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Extensive review of microwave filter tuning techniques with a novel tuning Technique based on Dezert–Smarandache theory and machine learning

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ABSTRACT

The rapidly growing demand for connectivity has necessitated the efficient production of microwave (MW) filter units, where the critical step of tuning these filters often becomes a bottleneck due to its traditional manual process. This research aims to explore and evaluate various MW filter tuning techniques proposed by researchers, highlighting their limitations and providing a comparative analysis. To this end, approximately 200 research papers from various journals and conferences were systematically reviewed to gather insights into existing MW filter tuning methodologies. The review revealed that while numerous techniques exist for MW filter tuning, each has limitations that hinder its universal applicability. Many traditional methods are labor-intensive and require expert intervention, leading to inefficiencies in filter production. The paper ends with the implementation of Dezert–Smarandache Theory (DSmT) and Machine Learning (ML) based filter tuning algorithm. This approach not only addresses bottlenecks in filter production but also paves the way for future advancements in automated tuning technologies. In nutshell, the comprehensive comparative analysis provided in this paper serves as a valuable resource for researchers and practitioners seeking to enhance MW filter tuning processes.

1. Introduction

Communication filters working in Microwave (MW)/Radiofrequency (RF) range are essential for isolating specific frequencies from a broad spectrum, are pivotal for wireless systems working in domain of space and terrestrial communications (Hunter et al., 2002). The exponential growth in telecommunication demand has necessitated the production of diverse MW/RF filters, among which coaxial cavity band-pass filters are predominantly utilized in Wireless Base Station (WBS)/Radio Base Station (RBS)/Base Transceiver Station (BTS) installations (Mansour, 2004).

Each filter's casing contains multiple coupled resonators (Cohn, 1957). Higher-order filters with cross-coupling between non-adjacent resonators are prevalent in real-world applications due to their ability to meet stringent frequency requirements (Macchiarella, 1997). The most common way to introduce cross-couplings in the resonators is to design the filters with cascaded structures, among which the most popular choice among filter designers are cascaded triplets (CT) (Yildirim et al., 1999) and/or cascaded quadruplet (CQ) (Levy, 1995). The presence of cross-couplings introduces Transmission Zero(s) (TZ) (Brian Thomas, 2003) (Amari and Bornemann, 2000) (Yildirim et al., 2002) in the frequency response, i.e., they assist in achieving sharp frequency transitions between pass band and stop band. Also, TZs enhance design flexibility, provide optimal in-band response, and reduce filter size, thereby paving the way for more efficient and cost-effective wireless communication solutions. Design of cross-coupled filter using Neural Networks (NNs) and equivalent circuit model of filter was presented in (Wang et al., 2006). This novel understanding underscores the evolving strategies in filter design, reflecting a continuous advancement to meet the escalating demands of modern telecommunication systems.

The tuning process is inevitable to compensate for the errors introduced during designing phase, manufacturing phase, assembly phase and because of the variation in the material of these filters. Presence of one or more of these errors lead to deviation of the desired frequency response from the measured one (Ruiz-Cruz et al., 2008) (Snyder, 2007a) (Snyder, 2007b). For tuning the filters, the designers make provisions to add 'tuning elements' within the filter structure. Changing the position or insertion depth of these tuning elements changes the resonant frequency and/or electromagnetic coupling strength between neighboring or distantly placed coupled resonators. The precise adjustment of these tuning elements is crucial because even minor

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deviations can lead to substantial discrepancies in the filter's performance, making filter tuning an iterative, intricate, and time-consuming process. When it comes to more advanced filters, such as higher-order configurations with cross-coupled topologies, the tuning time and tuning complexity rise exponentially due to complex relationship between the physical movements given to the tuning elements and the filter's frequency response (Han et al., 2010).

Historically, a range of methods, including electronic tuning, magnetic tuning, and mechanical tuning, have been employed to tune the filters. For altering the frequency response of electrically tunable filters (which offer limited power-handling capacity), MEMS (micro-electromechanical system) technology is most widely used for tuning purposes (Makimoto and Sagawa, 1986) (Collodi et al., 2023). Magnetically tunable filters are also commonly used in applications requiring high Q-factor (Quality-factor) and a wide tuning range (Tanbakuchj et al., 1989) (Asci et al., 2020). The tuning of dielectric resonator cavity filter is controlled by moving the discs (often provided with holes) above the resonators (Panaitov et al., 2005) (Pance and Rochford, 2008). The frequency of stripline filters is achieved during their design phase only (Singh et al., 2024).

Mechanical tuning, which uses tuning screws, is the most common approach used for tuning the cavity filters. Usually, metallic screws are integrated into the casing of the commercial cavity filter units to alter the frequency response. These metallic screws are called as 'tuning screws' and are typically coated with a thin layer of silver to increase the conductivity (Sekhri et al., 2023a). The other screws that are used to hold the filter's top plate are 'mounting screws' (Sekhri et al., 2023b).

Since a wide variety of cavity filters (differing in terms of layouts, topologies, operating frequencies, ripples, transition band requirements, method of tuning, type of tuning elements used, etc.) are commercially available, the filter tuning process is neither universal, nor can generalize. Rather, each filter type requires a specific approach to tuning to achieve optimal performance. The design of the filter also influences the frequency response of the filter (Chuma and Mirshekar-Syahkal, 2002), (Yao et al., 1996). These factors must be carefully considered to ensure the desired frequency response is achieved.

The deterministic nature of the tuning process necessitates the involvement of skilled human operators, known as tuning experts. These specialists monitor the filter's scattering parameters (S-parameters) response on a Vector Network Analyzer (VNA). Some rules that can help these specialists exist, such as those discussed in (Lindner et al., 2006), but all the complete heuristic information needed cannot be comprehended in instructions alone. Therefore, extensive training is necessary to acquire these skills. Completing this training does not, however, mean that one will be adept in this case, since some individuals find difficulty in tuning even simple filters after months of training. Such tuning experts are not recognized as MW engineers, and the success of the tuning efforts by these experts depends mostly on their experiences and education. Additionally, an expert at tuning one kind of filter might not be able to tune another kind of filter. The industry's ongoing demand for competent and skilled tuning experts adds to the challenge, as recruiting new tuning experts has been a daunting task for industry. The physical demands of tuning often lead to wrist injuries among experts, resulting in significant healthcare costs for the industry due to necessary surgeries (Goyal, 2022). Hence, there is a need to automate this process, which can assist in lowering production costs, increasing tuning efficiency, removing human dependence, eliminating human errors, and shortening filter production times. Also, finding automated methods of post-production tuning of the filters is important, as this process is a bottleneck while automating the filter production line in the era of 5G and Industry 4.0 (Ruiz-Sarmiento et al., 2020).

The efforts to develop automated or semi-autonomous approaches for filter tuning started in the early 1990s. In 1994, COM DEV Ltd. introduced intelligent software for filter tuning that relied on parameter extraction techniques (Yu, 1994). The software was implemented into production lines by 1995 to aid experts in tuning satellite multiplexers (Yu, 2006) and was later modified and renamed 'RoboCAT' (Yu, 2003). By 2003, RoboCAT was used for tuning commercial diplexers (Yu, 2003), where non-linear optimization techniques were employed for extracting the Coupling Matrix. However, it should be noted that the tuning solution introduced by COM DEV Ltd. was far from flawless. In particular, the decision was script-driven; the tuning process was too long; once the algorithm crosses the pre-defined time limit, the algorithm was defined to restart the tuning. Also, the scenarios with the full insertion or removal of the tuning screws were not considered in this work. These facts assert that the solution presented by COM DEV Ltd. was neither fully autonomous nor semi-autonomous.

Later, a method in which computer is used to suggest the optimal tuning strategy was presented in (Macchiarella and Santoniccolo, 2001) in which the actual tuning process was carried out by a human operator. Recently, a complete solution for autonomous filter tuning of cavity filters without human intervention at any stage was presented in (Yiğit and Afacan, 2023). The control architecture used in this work was described in (Yigit and Suvak, 2022). However, the authors only provided a theoretical solution to the problem. The actual tuning of filters was kept as a future scope for (Yiğit and Afacan, 2023).

Starting from early 1950s, numerous filter tuning solutions have been proposed by the research community. A review paper specifically dedicated to the compilation of various filter tuning methods related to low-pass LC filters was presented in 1991 (Jervis and Crofts, 1991). This paper reviews various filter tuning techniques proposed by research scholars working in this domain between 1951 and 2024. The authors presented the categorization of various filter tuning techniques and discussed the publications published in each category in detail. The prime focus of this research paper is to review the techniques relating to the tuning of band-pass filters. Master and Ph.D. thesis directly related to this topic are also reviewed. Active filters, ferroelectric filters, and superconducting filters have been kept beyond the scope of this paper. To avoid copyright conflicts, patents related to filter tuning process are also considered in this document.

The structure of the remainder of this research is outlined as follows, Section II provides an extensive review of the existing literature on filter tuning, offering a broad perspective on the field. Section III undertakes analysis of various categories of filter tuning techniques highlighting their key limitations and also explores the latest trends and advancements in filter tuning technology. Section IV presents a novel filter tuning method based on DSmT and ML. The final section consolidates the insights gained from the research, reflects on the progress made in the field, reiterates the importance of continued innovation, and outlines prospective avenues for future research.

2. Review of related literature

The research community, actively working towards efficient ways of tuning the MW filters, presented numerous filter tuning techniques. The authors of this current work considered the filter tuning techniques proposed between 1951 and 2024. Fig. 1 shows the categorization of these techniques. This section of the paper will discuss the methods presented in each category sequentially.

2.1. Tuning the filters in time domain

The Time Domain (TD) tuning of MW filters involves transforming the frequency response of reflection characteristics S_{ii} (ω) into the time domain $S_{ii}(t)$ using Fast Fourier Transform (FFT). This transformation allows distinct 'dips' and 'peaks' to be observed, which correspond to individual resonators and inter-resonator couplings, respectively, as shown in Fig. 2 (right). The dips and peaks for $t < 0$ are redundant. The visualization of these features in the TD facilitates precise tuning of each resonator. Unlike the frequency domain, where such detailed cause-and-effect relationships are not apparent, as evident from Fig. 2 (left), the TD approach provides immediate feedback about the component(s) causing

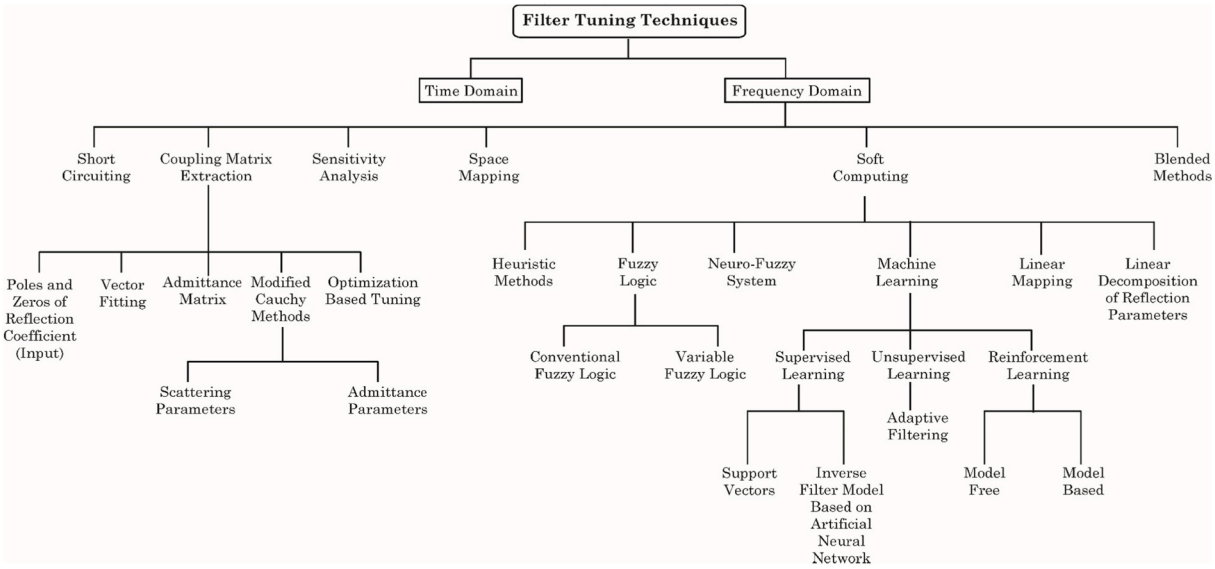

Fig. 1. Various filter tuning techniques.

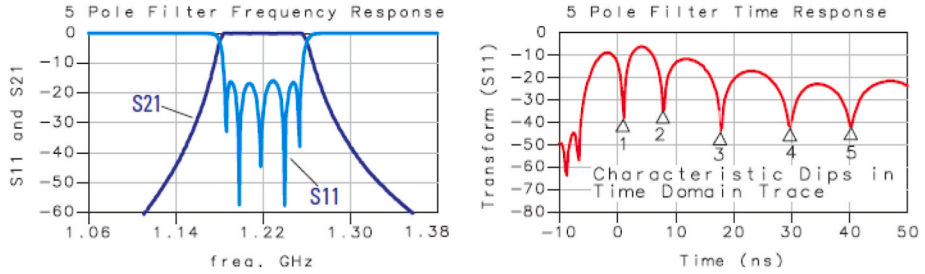

Fig. 2. Response of a filter in the Frequency Domain (left) and Time Domain (right) (Simplified Filter Tuning Using Time Domain, 1999).

the detuning of filter. Key developments in TD-based filter tuning are.

1. **Dunsmore's TD methods for tuning inline filters** (Dunsmore, 1999a) **and** (Simplified Filter Tuning Using Time Domain, 1999): Introduced the TD method for MW filter tuning by comparing the reflection characteristics (S_{ii}) of a perfectly tuned 'golden filter' with the filter under consideration. This approach was validated on a 5-cavity inline resonator filter (Simplified Filter Tuning Using Time Domain, 1999) expanded on the TD method presented in (Dunsmore, 1999a) with additional examples demonstrating its application to all-pole band-pass filters. It showed that adjusting each screw affected specific parts of the response curve, with the depth of dips related to the extent of resonator tuning.
2. **Dunsmore's TD methods for tuning cross-coupled filters** (Dunsmore, 1999b) **and** (Network Analysis Solutions Advanced Filter, 1999): Addressed the tuning of cross-coupled filters using the TD method using the theoretical steps discussed in (Simplified Filter Tuning Using Time Domain, 1999). However, it was found that the depth of the dips did not always accurately represent the tuning state of the filter for cross-coupled filters. The use of a 'golden filter' or simulated S-parameters became necessary for accurate tuning of such filters.
3. **Advanced TD-based tuning method** (Burger and Hoeft, 2014): This method addresses the key common limitation of (Dunsmore, 1999a), (Simplified Filter Tuning Using Time Domain, 1999, Dunsmore, 1999b), and (Network Analysis Solutions Advanced Filter, 1999), i.e. to determine the tuning direction, the authors of (Burger and Hoeft, 2014) used the phase of reflection parameters to determine tuning direction. This direction determination was based on the phase shift relative to the center frequency. This information, in addition to TD response magnitude, enabled quicker and more efficient tuning. However, this method was still limited to low-order all-pole filters and was not applicable to commercially used complex filter designs.

2.2. *Tuning the filters in frequency domain*

The tuning methods based on Frequency Domain (FD) use forward and/or reflected scattering parameters (i.e., S_{ji} and/or S_{ii} respectively) to tune the filters, as opposed to TD methods (in which only use refection (S_{ii}) parameter of the filters for tuning). A simulated FD response is depicted in Fig. 2 (left), representing the insertion loss (dark blue) and return loss (sky blue) for a 5-pole filter.

1)Short-Circuiting based Filter Tuning

The publications in this category discuss various tuning methods by either 'shorting' (or strongly detuning) the resonators and/or by presenting the idea of tuning resonators and coupling screws in a particular order for simplifying the tuning process. Such a method allowed the possibility of reducing time elapsed in tuning the filter and difficulty involved in tuning the filters. Various publications falling under this tuning method are.

1. **Early Sequential Method** (Dishal, 1951): Introduced an alternate short-circuiting technique to minimize return loss by tuning from the input connector to the output connector of the filter while observing the voltage values at the center frequency. This method, which was effective for the filters irrespective band

(frequency response), was manual, coupling value information was not available; it required a loosely coupled detector for amplitude measurements; and it was highly iterative.

2. Atia and Williams (1975): Built upon previous method presented in (Dishal, 1951) by measuring resonant frequencies and inter-resonator coupling using filter synthesis techniques (Atia et al., 1974). In (Atia and Williams, 1975), constant resonant frequency was achieved by manually tuning the resonators synchronously. Although the method was accurate, the condition of achieving constant frequency made this process time-consuming, particularly for filters with varying resonant frequencies and complex cross-coupled cavities. This approach was later adapted for singly and doubly terminated filters (Chen, 1977).
3. **Phase Response-based Tuning** (Williams et al., 1983)**:** This method was built on (Atia and Williams, 1975) which used phase response of S_{11} parameter to calculate inter-cavity coupling between resonators. It needs sequential tuning of the coupling elements starting from input side to output side. In general, the method was good and paved path for automatic filter tuning process. This method does not work well if the extracted response is far from desired value.
4. **Computer Aided Tuning System** (Accatino, 1986): Authors used the tuning methodology presented in (Atia and Williams, 1975) and combined LCX synthesis to determine inter-cavity couplings and resonant frequencies for a short-circuited network but required frequent cable changes for connecting I/P and O/P probes of each cavity and prior calibration, making the process complex and less practical. Also, there was a need to run the pattern search optimization for optimizing the singularity of the filter transfer function.
5. **Ness's Absolute Reflected Group Delay Methods** (Ness, 1998a) and (Ness, 1998b): These methods proposed a novel sequential tuning approach from the input to the output end which uses magnitude of the reflected Group Delay (GD) of reflection characteristics for tuning highly detuned resonators. The proposed tuning method was effective for inline filters, but it was complex and impractical for cross-coupled filters. This method in (Ness, 1998b) was the extended version of (Ness, 1998a) and could deal with cross-coupled filters but the overall process was complex.'
6. **Hilbert Transformation Based Relative Group Delay Method** (Zahirovic and Mansour, 2008): The authors measured relative GD derived using the Hilbert Transformation (Perry and Brazil, 1996) of transmission characteristics with the help of a scalar network analyser. This reduced VNA related costs but compromised precision with incomplete detuning (careful shorting), making this process ineffective for higher-order filter tuning.
7. **Adaptive Model Based Tuning Methods** (Pepe et al., 2004) and (Pepe et al., 2005): In these methods, both input and output reflection coefficients were used for tuning, offering flexibility since tuning from both sides was possible. These non-linear optimization-based algorithms could provide information about the amount of detuning along with the information of the detuned parameter. However, the need for optimization routines made this method time-consuming and limited to moderately complex in-line and waveguide filters mainly.
8. **Frequency Domain Data Cloning** (Lindner et al., 2007)**:** A sequential tuning concept for cross-coupled filters was developed based on frequency domain data cloning using the circuit model presented in (Atia and Williams, 1975). The couplings were coupled to a weak tuning state, whereas the resonators were shorted. The filter was tuned sequentially from starting from outer screws at both sides and gradually moving towards the center one. Although this method showed potential, it was limited by the need for precise frequency cloning, increased complexity due to cross-coupling placements, bandwidth limitations, and the necessity of human intervention.
9. **Neural Network-Based Method** (Michalski, 2011): Presented a Neural Network (NN) inverse model to map S_{11} parameters of filters to tuning screw positions by detuning each tuning screw in both directions. For tuning the filter, it was required to move from input connector to the output connector. While innovative, it required extensive training data, which limited the industrial implementation of this technique.
10. **Robotic Computer-Aided Tuning** (Wei et al., 2015): In this master thesis, the author sequentially tuned the resonators of a coaxial filter from I/P side to O/P side. For this, phase format was used and 0° and $\pm 180^\circ$ crossings were observed. However, this step could only be used for 'coarse tuning' of the filter.
11. **Sequential Tuning using Fusion Algorithm** (Sekhri, 2024): In this Ph.D. thesis, the author used theoretical knowledge and AI to tune all-pole in-line coaxial filter. Before tuning, all the resonators were shorted and then the tuning process was initiated. In terms of tuning direction, the fully automated tuning robot tuned the cavity filter from I/P side to O/P side. For tuning, two different plots – polar chart and Smith chart were used. For tuning using Smith chart, a parametric tracking approach (Sekhri et al., 2023c) was used to fetch the current tuning state of the filter. The dataset (Sekhri 2023) was curated for implementing this approach. However, this approach was tested only on iris-coupled filters only.

Thus, each of these short-circuiting-based methods offer unique advantages and limitations, aiming to simplify and expedite the filter tuning process. A short summary of the shorting-based filter tuning methods is presented in Table 1 which shows the filter topology on which each method was validated. The table also depicts if a particular strategy was used for tuning cross-coupled filters or not.

Table 1
Summary of various short-circuit based filter tuning techniques discussed in this review.

Reference	Year	Plotting Curve Used	Type of Filter used for Validation	Tuning cross-coupled filters
Dishal (1951)	1951	Group Delay	Waveguide Filter	No
Atia and Williams (1975)	1975	Polar Plot	Waveguide Filter	Yes
Chen (1977)	1977	Polar Plot	Waveguide Filter	No
Williams et al. (1983)	1983	Polar Plot	Not mentioned	No
Accatino (1986)	1986	Polar Plot	Waveguide Filter	No
Ness (1998a)	1998	Group Delay	Combline Filter	Yes
Ness (1998b)	1998	Group Delay	Combline Filter	Yes
Zahirovic and Mansour (2008)	2008	Group Delay	Waveguide Filter	No
Pepe et al. (2004)	2004	Phase Plot	Waveguide Filter	Yes
Pepe et al. (2005)	2005	Phase Plot	Waveguide Filter	Yes
Lindner et al. (2007)	2007	Polar Plot	Not mentioned	Yes
Michalski (2011)	2011	Real Input Reflection Coefficient Re (S_{11})	Diplexer (Coaxial Filter)	Yes
Wei et al. (2015)	2015	Phase Plot	Coaxial Filter	Yes
Sekhri (2024)	2024	Polar Plot and Smith Chart	Inline Coaxial Filter	No

2) Filter Tuning based on Coupling Matrix Extraction

Modern filters are based on the Coupling Matrix (CM) model presented in (Atia and Williams, 1971). The CM represents GD and FD, with its elements directly corresponding to tuning elements. Effective filter tuning may be based on extracting CM values (also known as 'filter diagnosis' or 'parameter extraction') to compare the desired and actual CM, which guides the tuning direction and adjustments. This category actively talks about two important terms, i.e., unloaded Q (Q_u) and external Q (Q_e). For quick recall of the reader, the Q_u value defines the limitations of applications for a MW resonator, and the Q_e value narrates how the resonator will interact with other MW devices within system. A method to measure Q_u and Q_e is presented in (Kwok and Liang, 1999). Various filter tuning algorithms based on extracting the CM are as follows.

a) Parameter Extraction using the location of Poles and Zeros of input reflection coefficient (S_{11})

This technique involves initially inserting tuning screws deeply into the filter cavities to create a significant difference between the initial and desired frequency responses. The filter is then tuned using either polar plots, phase plots, or Smith chart from a VNA. The process includes sweeping the frequency many times the bandwidth (BW) at the center frequency of the filter (f_0) and adjusting the phase reference plane to locate the zero point of the S_{11} before tuning begins. The research works published under this category are discussed below.

1. **Sequential Computer-Aided Tuning Algorithm** (Marquardt and Muller, 1977)**:** This approach uses regular network functions to relate filter response to tuning screw depth, providing a compensation matrix. It identifies poles and zeros based on the phase of S_{11}. For direct measurement, poles and zeros are the 0° and ±180° phase-crossings of S_{11}. Nonetheless, this tuning technique has limitations such as ineffectiveness with strongly detuned filters, the filter was tuned manually, and the method still needed fine-tuning of the filter.
2. **Phase Response-based Tuning** (Williams et al., 1983)**:** This method was the follow-up version of (Atia and Williams, 1975) which used phase response of S_{11} parameter to calculate inter-cavity coupling between resonators. The poles and zeros are fetched using the polar chart of the network analyzer. However, it needed pre-tuning for the screws.
3. **Frequency Domain-Based Method** (Atia and Yao, 2000): This method, an extension of earlier work presented in (Atia and Williams, 1975), determines resonant frequencies and inter-cavity couplings by comparing extracted values with measured data without finding the location of the poles and zeros using phase crossings of 0° and ±180°. Instead, both of these entities were determined from pole frequencies and zero frequencies of input impedance of resonators shorted at one port. This was suitable for cross-coupled cascaded filters but limited to lower-order filters due to their inability to handle strong dependencies between neighboring resonators.
4. **Extended Methods** (Hsu et al., 2002a) and (Hsu et al., 2002b): These methods were the extended version of (Atia and Yao, 2000) and refined filter tuning by removing phase-loading effects and using closed-form recursive formulas. They rely on phase derivatives for accurate pole and zero determination, as in (Ness, 1998a). Despite improvements, they still face issues such as unaddressed phase shifts, reliance on mathematical models that were not exact, and practical limitations like the need for additional transmission lines at the O/P or I/P port of the filter because the reference plane for phase measurement was not easily accessible.
5. **Coupling Matrix Rotation-based Method** (Ghadiya and Soni, 2014): This method also required additional transmission length as it was in (Hsu et al., 2002a) and (Hsu et al., 2002b) and introduced "coupling matrix rotation" as a concept. This method was applied to Dielectric Resonator (DR) filters and developed a simple computer program for CM extraction in which loss for each resonator was consistent. However, it was limited to specific filter topologies and may not be broadly applicable.

In general, the procedure for using poles and zeros for filter tuning is highly iterative and the accuracy of the extracted parameters directly depends on the precise determination of pole and zero locations. As the number of resonators increases, errors also increase, making this technique unsuitable for higher-order filters. Additionally, the system's accuracy heavily relies on the calibration procedures used to define the reference plane for phase measurements.

b) Parameter Extraction using Admittance Parameters (Y-Parameters)

The output obtained from a MW filter when connected to VNA is in the form of S-parameters, from which one can obtain a scattering matrix (S-matrix) (Kurokawa, 1965). But some researchers proposed the conversion of these S-parameters to Y-parameters for tuning the filters, as Y-parameters have reduced dimensions, are more accurate, and possess better model sensitivity. The transfer function of Y-parameters can then be synthesized easily to fetch the corresponding CM by the techniques proposed in (Cameron, 1999) and (Cameron, 2003) using the information about obtained poles and residues (i.e. residues of poles). Various parameter extraction methods based on Y-parameters are summarized as follows.

1. **Basic Analytical Method** (Meng and Wu, 2006): The analytical methods of extracting CM using partial-fraction expansion of the Y-parameters used in (Meng and Wu, 2006) were initially reported in (Meng and Wu, 2005). The notion of constant phase-loading was introduced without needing extra calibrations to determine the loading effects but had limitations such as a lack of detail on determining the constant value in phase-loading, a basic procedure for extracting the Q_u value, and applicability only to lossless cases. Follow-up work (Kabir et al., 2010) used neural networks for filter modelling but still faced limitations.
2. **Advanced Phase-Loading Method** (Meng and Wu, 2009a): The detailed theory and implementation of the phase-loading concept introduced in (Meng and Wu, 2005), (Meng and Wu, 2006) and (Meng and Wu, 2009b) was elaborated by the same research group. This method enhanced the CM extraction process for lossy filters with non-uniform Q_u values. It provided information on de-embedding techniques for unknown transmission line sections and addressed degenerate poles in terms of Y-parameters. The process was deterministic, requiring no initial value guesses, but it had limitations, including the inability to handle Source-Load (S-L) coupling, challenges with phase-shift removal, restricted applicability to filters with a short variation range for Q_u, and suitability mainly for low-loss filters as the poles were not easily distinguished from the magnitude of Y-parameters. Additionally, the assumption of 'pure real residues' while extracting the 'imaginary portion of poles' of the Y-parameters limited its use for filters with non-uniform Q values.
3. **Refined Method with S-L Coupling** (Wang et al., 2014): To address issues from (Meng and Wu, 2009a), namely dealing with degenerate poles and S-L coupling, this method dealt with lossy cross-coupled filters and measurement noises. After removing phase-shift effects of the measured S-parameters caused by the unknown length of the transmission lines at I/P and O/P ports, characteristic polynomials were obtained using the S-parameters-based modified Cauchy method (discussed later in this paper). For obtaining CM and unloaded Q_u, these S-parameters were converted to Y-Parameters using the conversion procedures presented in (Cameron et al., 2007)

for obtaining CM and unloaded Q_u. Despite improvements, inaccuracies in Q_u factors limited its efficiency.

4. **Y-Parameters-Based Cauchy Method** (Wang et al., 2015a): Y-Parameters-based modified Cauchy method (discussed later in this paper) to obtain the characteristic polynomials was expected to assist in extracting CM and determining uneven Q_u values without removing phase shift. This approach was tested for extracting CM from a lossy cross-coupled filter. However, it still faced challenges as phase-shift removal was still inevitable and there was a need to carefully select the frequency points. Both of these factors impacted on the commercial viability of this method.

Using Y-parameter-based filter tuning was not apt for tuning the commercial filters as it also required the removal of phase loading effects for obtaining the poles and residues. Phase loading is not incorporated in the filter model used for filter diagnosis, but it is always present in a physical filter unit. Also, the accuracy of extracted Y-parameters is quite low when the filter is highly detuned.

c) Parameter Extraction using Vector Fitting Approach

The Vector Fitting (VF) approach (Gustavsen and Semlyen, 1999), also improvised in (Gustavsen, 2006), uses measured or numerically simulated data to create reduced-order models. Instead of directly fitting the data into polynomials, it generates an approximate rational function polynomial in the form of a partial fraction expansion. In principle, VF assists in relocating the poles to better locations iteratively, thus guaranteeing the stability of poles and zeros. Compared to other rational approximation methods, VF allows fast convergence even with fewer iterations. Researchers have therefore applied this methodology to the field of MW filter tuning.

1. **Method for Constant Q_u Filters** (Liao et al., 2007): This technique synthesizes Y-parameters for lossy cross-coupled filters using a transverse network model. It identified pole positions and residues, with real parts of complex poles providing approximate uniform Q_u using only the simulated S-parameters. The residues of partial expansion of the Y-Parameters were assumed to be real. The authors of this method discussed the diagnosis of filters with S-L coupling but did not provide any examples to support their claims. Another limitation of their work was the assumption that the Q_u value remains constant, which is not accurate for commercial filters.
2. **Method for Uneven *Q*u Filters** (Hu and Wu, 2014): This approach was aimed at dealing with lossy filters having uneven unloaded Q-values. It was aimed at extracting complex poles and residues and accurately determining the Q_u values. It solved rational polynomials of Y-parameters derived from measured or simulated S-parameters. Key issues included specifying frequency samples only on the positive side, errors in band-pass to low-pass transformations of poles and residues obtained, and the iterative nature of process of finding the poles and residues.
3. **Modified VF Method** (Ng et al., 2023): For replacing partial fractions being used as a basis function, a model-based VF method was proposed for extracting the CM of diplexers, as discussed in (Zhao and Wu, 2016a). Recently, a method that introduced focus fitting and pole forcing alongside the conventional VF method to improve the accuracy of S-parameter response approximations was presented in (Ng et al., 2023). This method used conventional S-parameters instead of the Y-parameters used in (Liao et al., 2007) and (Hu and Wu, 2014).

In general, to extract a correct CM using VF methodology, matrix transformations are further needed, like the one proposed in (Kozakowski et al., 2005). Alternatively, the extracted CM needs further optimization, as the one i.e., Non-Linear Polynomials (NLP) optimization presented in (Ng et al., 2023). But VF method usually needs positive frequency samples only for parameter extraction, hence making it unsuitable for a CAT system.

d) Parameter Extraction using Modified Cauchy Method

The Simple Cauchy Method is a technique used to convert measured or simulated S-parameters of lossless, reciprocal 2-port passive devices into reduced-order rational functions (Adve and Sarkar, 1993) even with fewer data samples (Dhaene et al., 1995). A short explanation of this method is as follows:

The method converts S-parameters into rational functions using a reduced number of data samples. It starts with a band-pass (BP) response and generates a polynomial model in the low-pass (LP) frequency domain with minimal order and error (Adve et al., 1997). The number of resonators and TZs define the degree of characteristic polynomials. It uses a Vandermonde Matrix to simplify equations. For microwave (MW) filters, the method was modified to fit two S-parameter sets (S_{11} and S_{21}) simultaneously. To preserve useful information, S-parameters are required to share a set of common poles (Matthaei et al., 1964). The characteristic or filtering function '*K(s)*', which is the ratio of Transmission Zero (TZ) to Reflection Zero (RZ), make sure that sets of zeros do not include filter losses. Total Least Squares (TLS) (Van Huffel and Vandewalle, 1991) and Singular Value Decomposition (SVD) (Stewartt, 1993) are used to solve the equations. TLS provides optimal solutions even with noisy data, and SVD provides the capability of dealing with overdetermined systems. The characteristics of polynomials are solved in two steps.

i. Determining Numerator Coefficients – using TLS and/or SVD.
ii. Determining Denominator Coefficients – using Feldkeller's energy conservation equation.

For filter diagnosis, researchers have proposed two variations of the modified Cauchy methods – S-parameters-based, and Y-parameters-based and the research efforts made in each of them are as follows.

(1) S-Parameter-based Modified Cauchy Method

1. **Basic Filter Modelling Methodology** (Lamperez et al., 2002): This method utilizes both S_{11} and S_{21} simultaneously to model filters, considering Source-Load (S-L) coupling coefficients. This method employs TLS for solving systems but has limitations, including the lack of guaranteed stability and lack of constraints outside the measurement frequency band. The scope of this work was limited to filter modelling itself but laid foundation for filter tuning using this approach.
2. **CM Extraction using an Efficient Algorithm** (García-Lampérez et al., 2004)**:** The methodology from (Lamperez et al., 2002) was adapted for filter tuning using an efficient algorithm based on model optimization. It generated polynomial models of S-parameters using simplified TLS and SVD. The algorithm derived two types of coupling matrices – extracted and desired, comparing which errors in vertical position of tuning screw could be related. The key limitations were – the method could tune very simple cross-coupled filters only, tuning screws were pre-set, lossless measured data was needed in this methodology, using *K(s)* necessitated posterior reconstruction of common poles, and method could be implemented to filters with minimal losses.
3. **Improved CM Extraction using Constraints** (Lampérez et al., 2004): This work improved on (García-Lampérez et al., 2004) by using the Constrained TLS Method and eliminating *K(s)*. Also, it addressed lossless and lossy filters but offered limited capabilities for diagnosing filters with S-L coupling and handling second-order effects. It also had issues with phase-shift effects and realizability of TZs. In addition, the authors also talked about removing losses from the extracted

polynomials, but the process proposed by them was slow or had lower accuracy.

4. **Tuning Filters with Realizable Transmission Zeros** (Macchiarella and Traina, 2006)**:** To address the limitations in (Lampérez et al., 2004), researchers proposed a method involving realizable TZs. The proposed model (reduced order) could work with lossless as well as lossy measurement data. Like (García-Lampérez et al., 2004), TLS and SVD were jointly used for obtaining accurate polynomial characteristics. This method required frequency points to be chosen near the desired band and still could deal with filters having low to moderate losses.
5. **Optimization-Free Improved Cauchy Method** (Traina et al., 2006)**:** The research efforts presented in (García-Lampérez et al., 2004) - (Macchiarella and Traina, 2006) were applied to tuning of commercially used GSM filters. Matrix rotations (Tamiazzo and Macchiarella, 2005) were needed while synthesizing the CM. The method could successfully identify detuned elements with the differences between values of coupling matrix elements in desired and extracted CMs. Like (García-Lampérez et al., 2004) and (Macchiarella and Traina, 2006), the proposed approach involved solving equations with TLS and SVD. Using a golden filter unit provided the tuning sequence but the methodology was limited to pre-tuning stages.
6. **CM** Extraction **Using Eigenvalue-Based Optimization** (Esmaeili and Borji, 2010): This method improved the accuracy of extracted characteristic polynomials of lossy filters by removing losses by shifting the poles and zeros of *K(s)*. The final CM was extracted using eigenvalue-based optimization (Kozakowski et al., 2005). The method in (Lamecki et al., 2004) also used eigenvalues information in CM extraction process. The method presented in (Esmaeili and Borji, 2010) addressed some issues from previous methods like (García-Lampérez et al., 2004), (Lampérez et al., 2004), (Macchiarella and Traina, 2006), and (Traina et al., 2006) and provided the value of external *Q* of the filter but assumed uniform unloaded *Q* values and was restricted to low-loss filters.
7. **Accurate CM Extraction with Modified Band-pass to Low-pass** (Macchisrella, 2010): This work advanced the method to handle large losses by using modified band-pass to low-pass transformations and solving polynomial equations using *K(s)* with TLS and SVD. This method faced challenges with uneven Q_u, diagnosis of S-L coupling, dealing with second-order effects but improved handling of resonator losses.
8. **CM extraction After Phase-Shift Removal** (Wang and Xu, 2011a)**,** (Wang and Xu, 2011b) and (Wang et al., 2011): An accurate CM can only be extracted when phase-shift effects are removed (Cameron, 2003). The other methods to remove the phase-shift effects like the ones proposed in (Hsu et al., 2002a), (Hsu et al., 2002b) and (Meng and Wu, 2009a) either need additional transmission line or need special considerations while selecting the sampling points. The methods presented in (Wang and Xu, 2011a), (Wang and Xu, 2011b) and (Wang et al., 2011) focused on removing phase-shift effects using Genetic Algorithm (GA) optimization by with minor changes in the steps. These methods improved accuracy of CM and filter's Q values. All these methods used domain transformation presented in (Macchisrella, 2010) and method presented in (Lampérez et al., 2004) to fetch the characteristic polynomials in single steps using TLS and SVD methods. These methods exhibited limitations such as choosing frequency samples near the desired passband, assuming uniform Q_u values for all the resonators, complex time-consuming optimization procedures.
9. **CM Extraction Using Differential Evolution and Particle Swarm Optimization** (Cao et al., 2018a): Authors introduced Differential Evolution (DE) and Particle Swarm Optimization (PSO) for accurate filter modelling, addressing uneven Q_u and non-ideal effects. DE provided fast convergence without getting influenced by initial values. Characteristic polynomials were obtained using TLS and SVD and then CM was synthesized. This method gave better accuracy as compared to (Wang et al., 2011) but had limitations with highly detuned states and the assumption made regarding equality in forward and reverse characteristics.
10. **CM Extraction using Y-Parameters with S-Parameters-based Cauchy** Method (Wang et al., 2014) and (Zhao and Wu, 2016b)**:**
    A. **Using Optimization** (Wang et al., 2014): This method considered S-L Coupling and used one step SVD for filter diagnosis. After removing phase shift with GA optimization, the characteristic polynomials were obtained, which then helped in calculating Y-parameters using empirical formulas. Further, CM was extracted for the considered filter topology. The method could handle filters with non-uniform Q_u, but the obtained Q_u values were inaccurate. This research considered only S_{11} and S_{21} parameters.
    B. **Without Optimization** (Zhao and Wu, 2016b): This was the first method that considered S_{11}, S_{21}, and S_{22} data together. The rational polynomials were determined using Y-parameters which were then converted to S-parameters. Before extracting CM using TLS and SVD, a few matrix transformations given in (Guyette et al., 2006) were needed which made this process time-consuming and complicated.

(2) Y-Parameters-Based Modified Cauchy Method

Y-parameters offer reduced dimensions and enhanced stability for extracting the CM, eliminating the need to separately address filter losses and uneven Q values for each resonator, which is required when S-parameters are used.

1. **Method in** (Wang et al., 2015a)**:** Introduced the use of the Cauchy method exclusively in terms of Y-parameters. This method enables the extraction of characteristic polynomials U, V, and W in a single step without needing to separately account for filter losses. This method could deal with filters with non-uniform Q_u for each resonator without considering the filter losses separately. However, phase-shift effects still need to be removed, and accurate results require selecting frequency samples close to the desired passband.

In all research works utilizing the Modified Cauchy method (based on S-Parameter or Y-Parameter), the final step involves synthesizing the CM using well-established methods as presented in (Cameron, 1999), (Cameron, 2003), and (Cameron et al., 2007). Vandermonde matrix used in the Cauchy method is the key issue as it cannot deal with higher-order systems because the matrix becomes ill-conditioned, and its accuracy is degraded when the number of unknowns becomes high (Golub and Van Loan, 1996). Although strategies to address this issue have been discussed in (Traina et al., 2007), the accuracy remains insufficient. In (Traina and Macchiarella, 2007), a modification of the Cauchy method was introduced to handle higher-order systems by preconditioning the main matrix using an appropriate scaling technique. It was suggested in (Wilkinson, 1961) and (Bauer, 1963) that matrix equilibration is crucial for improving numerical computations. So, the method proposed in (Traina and Macchiarella, 2007) is lengthy, computationally intensive, and performs poorly under high detuning

levels. Additionally, the Cauchy method generally loses accuracy due to the presence of second-order effects.

e) Parameter Extraction Using Optimization Techniques

The basis of this filter diagnosis technique is to optimize the defined circuit model's parameters to ensure that the response it produces matches the intended response. By comparing the parameters (coupling values) between extracted CM and desired CM, the tuning element(s) responsible for the detuning can be identified and the defined objective function is minimized at the sampled frequency points. The process continues until the error between the extracted coupling elements and desired coupling elements is reduced to an acceptable value. This methodology allows tuning of all the elements, and the error is compensated at each iteration. The efforts of research community in the area of extracting the CM using optimization techniques are as follows.

1. **Optimization for Extracting Model Element Values** (Thal, 1978): This approach introduced a method to determine center frequencies and coupling coefficients using element optimization routines. The filter response was first measured and then fitting the best circuit model to match this response. The process was repeated until the desired response was achieved. This method could not be implemented in real-time, generalization to any other filter topology was not possible, the approach was time-consuming, precise calibration and pre-tuning was needed before tuning the filter.
2. **Gradient-Based Optimization for Tuning** (Harscher et al., 2000) and (Harscher and Vahldieck, 2001): These methods used an equivalent network model with lumped elements. Model values were extracted from S-parameters using gradient-based optimization to minimize the Mean Squared Error (MSE) between measured and simulated responses at specified frequencies. This algorithm optimized tuning elements and screw positions. However, it required pre-adjustments, careful selection of initial values, assumed linear S-parameter variations with frequency changes, needed the DUT response to be close to the desired response, and considered only the magnitudes of S-parameters.
3. **Generalized Filter Prototype Models** (Harscher et al., 2001a), (Harscher et al., 2001b) and (Lamecki et al., 2004): These methods used generalized filter prototype models for CM extraction, unlike the equivalent network models in (Harscher et al., 2000) and (Harscher and Vahldieck, 2001). Both methods ((Harscher et al., 2001a) and (Harscher et al., 2001b)) considered the magnitude and phase of S-parameters, modelling the phase shift by I/P and O/P probes with transmission lines. A non-linear gradient-based optimization minimized the MSE between extracted and desired responses, and the extracted parameter values were used to adjust the tuning screws. After sensitivity analysis, optimal parameter values were determined. However, Pre-tuning of filters was essential
4. **Model-Based Parameter Estimation** (Kahrizi et al., 2000), (Kahrizi et al., 2002) and (García-Lampérez et al., 2004): In these methods Model-Based Parameter Extraction (MBPE) technique (Miller and Burke, 1991) was used to reduce frequency-domain responses to polynomial coefficients for obtaining TZs and RZs. MBPE technique minimized the cost of measurements and computations. In (Kahrizi et al., 2000) and (Kahrizi et al., 2002) Sequential Quadratic Programming (SQP) (Boggs and Tolle, 1995) was used in these methods. Even if the locations of RZs and TZs were optimized, the ripple and return losses were not considered. Also, these methods had limitations in terms of accuracy, pre-tuning requirements and were restricted to low-loss filters.
5. **Non-Linear Optimization for Finding Detuning** (Pepe et al., 2004) and (Pepe et al., 2005): Research in (Pepe et al., 2004) and (Pepe et al., 2005) provided non-linear optimization algorithms for determining detuned parameters and amounts of detuning. These methods were effective for low-order simple topology filters only because they were time-consuming.
6. **Pattern Search Optimization Methods** (Accatino, 1986): The method in (Accatino, 1986) (later used in (Atia and Yao, 2000)) optimized resonant frequencies and inter-cavity couplings but it was basic, took long time, and was suitable only for lower-order filters.

The general issues with all the optimization-based filter tuning methods are.

- They fail to accurately detect spurious and unwanted couplings between neighboring elements.
- These methods struggle with highly detuned filters.
- Achieving global minima largely depends on the number of optimization variables and the quality of initial guesses.
- Finding the global minima is a complex process.

One way to address some of these issues is through an AI-based approach. An algorithm using a Multiple hidden layered Extreme Learning Machine (MELM) combined with a Differential Evolution Particle Swarm Optimization (DESPO) algorithm was presented (Wu and Cao, 2019a) to develop a parametric model. Also, group of researchers designed a tuning model based on improved Back-Propagation Neural Network (BPNN); Gauss Kernel Clustering (Wu and Cao, 2019b) where the Shuffled Frog-Leaping algorithm optimizes the weights of the BPNN architecture. These models might still not be able to solve the problem completely, but they can provide some assistance for tuning the filters. The problem of non-uniqueness (i.e., contradictions in O/P values with the same I/P) of the ANNs can be dealt with using multi-valued NNs (Zhang et al., 2018).

Another hybrid approach for modelling and tuning the coaxial inline filters, combining Convolutional Neural Networks (CNNs) and Elman Neural Networks was presented in (Bi et al., 2020). This optimized fusion method of filter modelling enhanced modelling accuracy and tuning performance with less sampling data compared to both modelling methods considered separately.

A short summary of the coupling matrix extraction-based filter tuning methods is presented in Table 2 which shows the filter topology on which each method was validated. The table also depicts if a particular strategy was used for tuning cross-coupled filters or not.

3) Space Mapping-based Filter Tuning

In 1994, Space Mapping (SM) approach was introduced to solve EM optimization problems related to designing MW stub filters (Bandler et al., 1994). Updates to this approach, namely Aggressive Space Mapping (ASM) (Bandler et al., 1995) and Neural Space Mapping (NSM) (Bandler et al., 1999), were then introduced in 1995 and 1999 respectively. The use of ASM for designing a microstrip filter was reported in (Bandler et al., 1996a). Yet another advancement in this approach, i.e. Implicit Space Mapping (ISM) was then introduced (Bandler et al., 2004a). Fundamentally, SM involves two separate models: a 'coarse model' i.e. a circuit-based (physics-based) computationally fast model exhibiting low accuracy, and a 'fine model' i.e. full-wave EM simulation based computationally intensive model with high accuracy. The coarse model handles the main optimization simulations, while the fine model is used for validation. Iterative updates of the mapping provide quick and accurate matching between both models. Details of the SM approach have been presented in (Bandler et al., 2004b) and (Koziel et al., 2008). A review of ISM-based methods for reducing the differences between the coarse model and the fine model by managing the preset parameters and continuously optimizing the coarse model to reach the defined ideal target was presented in (Cheng et al., 2015). Various techniques of filter tuning using space mapping are as under.

Table 2
Summary of various CM extraction based filter tuning techniques discussed in this review.

Parameter Extraction Technique	Reference Number	Year of Publication	Type of Filter used for Validation	Tuning cross-coupled filters
Location of Poles and Zeros of input reflection coefficient (S_{11})	Marquardt and Muller (1977)	1977	Waveguide Filter	No
	Williams et al. (1983)	1983	Not Mentioned	No
	Atia and Yao (2000)	2000	Not Mentioned	Yes
	Hsu et al. (2002a)	2002	Combline	Yes
	Hsu et al. (2002b)	2002	Microstrip Filter and Waveguide Filter	No
	Ghadiya and Soni (2014)	2014	Inline Coaxial (Dielectric Resonators)	Yes
Admittance Parameters (Y-Parameters)	Meng and Wu (2005)	2005	Waveguide Filter	No
	Meng and Wu (2006)	2006	2 Waveguide Filters	No
	Meng and Wu (2009b)	2009	Waveguide Filter	Yes
	Meng and Wu (2009a)	2009	3 Waveguide Filters	Yes
	Wang et al. (2014)	2014	Microstrip and Waveguide Filter	Yes
	Wang et al. (2015a)	2015	3 Microstrip Filters	Yes
Vector Fitting	Liao et al. (2007)	2007	Microstrip Filter	Yes
	Hu and Wu (2014)	2014	Waveguide Filter	Yes
	Ng et al. (2023)	2023	2 Waveguide Filters	No
Modified Cauchy Method	Lamperez et al. (2002)	2002	Microstrip Filter	Yes
	García-Lampérez et al. (2004)	2004	2 Waveguide Filters	No
	Lampérez et al. (2004)	2004	Waveguide and Microstrip Filter	Yes
	Macchiarella and Traina (2006)	2006	Combline	Yes
	Traina et al. (2006)	2006	Combline	Yes
	Esmaeili and Borji (2010)	2010	Waveguide Filter, Coaxial, and Combline Filters	Yes
	Lamecki et al. (2004)	2004	Waveguide and Microstrip Filter	Yes
	Macchisrella (2010)	2010	Waveguide Filter	No
	Wang and Xu (2011a)	2011	2 Microstrip Filters and 1 Coaxial Filter	Yes
	Wang and Xu (2011b)	2011	2 Microstrip Filters	Yes
	Wang et al. (2011)	2011	4 Microstrip Filters	Yes
	Cao et al. (2018a)	2018	2 Coaxial Filters	Yes
	Zhao and Wu (2016b)	2016	2 Waveguide Filters	Yes
	Wang et al. (2014)	2014	Microstrip and Waveguide Filter	Yes
	Wang et al. (2015a)	2015	3 Microstrip Filters	Yes
Optimization Techniques	Thal (1978)	1978	Elliptic Coaxial Filter	Yes
	Harscher et al. (2000)	2000	Coaxial Filter	No
	Harscher and Vahldieck (2001)	2001	Coaxial and Waveguide Filter	No
	Harscher et al. (2001a)	2001	Coaxial Filter	No
	Harscher et al. (2001b)	2001	Coaxial Filter	Yes
	Lamecki et al. (2004)	2004	Waveguide and Microstrip Filter	Yes
	Kahrizi et al. (2000)	2000	Combline	Yes
	Kahrizi et al. (2002)	2002	Combline	Yes
	Wang et al. (2014)	2014	Microstrip and Waveguide Filter	Yes
	Pepe et al. (2004)	2004	Waveguide Filter	Yes
	Pepe et al. (2005)	2005	Waveguide Filter	Yes
	Accatino (1986)	1986	Waveguide Filter	No

1. **Aggressive SM-based Tuning** (Rodriguez et al., 2017): ASM methodology was used to tune a 04-pole waveguide filter based on an electromagnetic model (EM). For ease of implementation and simplicity, ASM is commonly used in practical applications (Rayas-Sánchez, 2016). However, being computationally, the model took more time as compared to the total time taken for the direct measurements, limiting its commercial application in filter tuning.
2. **Simplified SM Approach** (Miek and Höft, 2018): A simplified SM approach (Muller et al., 2017) based 'Compensation Matrix' was used to relate Coupling Matrix (CM) elements to tuning screw deviations, improving iterative tuning. The coarse model had entries related to CM, whereas the advanced fine model had information about tuning screw positions. This method showed cross-dependencies between various adjacent elements. However, the method assumed linear relationships between CM elements and tuning screw depth and was restricted to simpler filters only.
3. **SM-based Systematic Tuning Procedure** (Melgarejo et al., 2019a): In this work, the authors established linear mapping between two spaces i.e. the insertion depth of tuning screws and actual dimensions of the DUT (a waveguide in their research work). The authors, via simulations, proved such a mapping could be achieved and the actual device did not need tuning. However, such a mapping is only possible for simpler filters only.
4. **Advanced Systematic Filter Tuning Approach** (Melgarejo et al., 2019b): The results obtained in (Melgarejo et al., 2019a) were used by the authors to effectively tune the filters. The authors compared the performance of five tuning methods. Assisting this approach with a reduced optimization space, the proposed methodology could tune the filter in a short time period. However, this methodology can again be applied to simpler filter structures only.

5. **Surrogate Model for Filter Tuning** (Li et al., 2019): The SM technique was employed to create a surrogate model for tuning the filter. The surrogate was developed using simulation software, while a physical component served as the fine model. In this approach, the tuning parameters had to be initially set to acceptable reference values. The initial parameters of the surrogate model were derived from datasheets and theoretical considerations. However, this pre-setting is not feasible when tuning real-world filters, and simulations alone cannot fully establish the tuning rules for actual filters.
6. **Improved SM Method** (Li et al., 2020): Instead of relying on EM-based model, to address the limitations of (Rodriguez et al., 2017) and (Li et al., 2019) and manage unexpected filter behaviour, the authors in (Lamperez et al., 2002) used a circuit-based coarse model instead of an EM model. This surrogate model combined an ISM-based coarse model with a linearly approximated measured response relative to tuning parameter changes from the reference point. Recursive multipoint parameter extraction techniques from (Bandler et al., 1996b) and (Bakr et al., 1999) ensured model reliability and unique solutions at each step. Robustness was improved by mapping the response and its first derivative concerning tuning parameters. Fine model perturbations, as introduced in (Brumos et al., 2014), were added when iterations failed. However, this work only considered a single reference point, making the model less reliable and the algorithm only converged when the defined reference point was close to the desired point.

A short summary of the space mapping-based filter tuning methods is presented in Table 3 which shows the filter topology on which each method was validated. The table also depicts if a particular strategy was used for tuning cross-coupled filters or not.

4) Filter Tuning based on Sensitivity Analysis

Sensitivity analysis, first highlighted by Bode in 1945 (Bode, 1945), focuses on how variations in parameters impact the function of a system, such as a filter's frequency response. The sensitivity in filter tuning helps map the impact of tuning screw adjustments on filter performance. Algorithmic approaches for tuning the filters using Sensitivity Analysis are as follows.

1. **Linear Search Techniques** (Pinel, 1971)**:** Introduced a CAT algorithm combining sensitivity analysis with linear search techniques to predict detuned element, tuning direction, and the amount (number) of adjustments required. The sensitivity of each variable component's response was calculated at specified frequencies, and the process involved adjusting a different component in each iteration until the desired response was achieved. This approach was superior to pattern-search methods but was limited by its reliance on perturbations from known values and lack of a contingency plan to deal with primary system failure.
2. **Sequential Filter Tuning Algorithm** (Marquardt and Muller, 1977)**:** A sequential CAT algorithm that utilized a compensation matrix and sensitivity matrix was proposed to establish the relationship between the filter response and the depth of the tuning screw. However, it faced challenges like needing repeated measurements, mandatory pre-tuning, and the involvement of human operators in performing the actual tuning. These factors limited the implementation of this process to fine-tuning stage only.
3. **Gauss-Newton Method** (Marshall and Tissi, 1991): This method offered a filter tuning algorithm that avoided complex modelling and calibration. The Gauss-Newton solution of the equations was used to determine the tuning adjustments needed to achieve the desired frequency response. This method required the coarse tuning to be performed by a method such as the one in (Dishal, 1951), thus limiting the effectiveness of this method to the fine-tuning stage only.
4. **Gradient-based Optimization Methods** (Harscher et al., 2000) **-** (Harscher et al., 2001b): These methods used equivalent circuit models to fetch optimized filter model values from measured scattering parameters for tuning the filters. Individual tuning screw's sensitivity was determined by respective element values in the model. However, the need to pre-tune the filter limits the tuning range of this method.
5. **Adaptive Model-Based Method** (Pepe et al., 2005): The method in this paper permits the systematic extraction of coupling coefficients, resonant frequencies, and resonator losses starting from a well-defined detuned condition. As a consequence of this particular feature, the algorithm allows tuning and diagnosis simultaneously. It, furthermore, offers a criterion to control the convergence of the alignment procedure. The process continued until the difference between desired CM and extracted CM is below the defined threshold. However, this process again used iterative optimizations to be performed, and a poor choice of initial variables led to solution trapping into local minima.
6. **Analytical Approach** (Meng and Wu, 2009a): This approach advocated for sensitivity analysis in Y-parameter-based CM extraction for lossless filters to minimize discrepancies between ideal and extracted coupling elements. However, again, this method was suitable for fine-tuning stage only.
7. **Surrogate Modelling-Based Method** (Li et al., 2019): This method employed sensitivity information to approximate solutions using surrogate models. But pre-characterization requirements restricted this method to fine-tuning stage only.

Table 3
Summary of various space mapping based filter tuning techniques discussed in this review.

Reference Number	Year of Publication	Type of Filter used for Validation	Tuning cross-coupled filters
Rodriguez et al. (2017)	2017	Waveguide Filter	No
Miek and Höft (2018)	2018	Inline Filter	Yes, but low-order filters only
Melgarejo et al. (2019a)	2019	Waveguide Filter	No
Melgarejo et al. (2019b)	2019	Waveguide Filter	No
Li et al. (2019)	2019	Waveguide Filter	No
Li et al. (2020)	2020	2 Waveguide Filters	No

Table 4
Summary of various sensitivity analysis based filter tuning techniques described in this review.

Reference Number	Year of Publication	Type of Filter used for Validation	Tuning cross-coupled filters
Pinel (1971)	1971	Not mentioned	No
Atia and Williams (1971)	1971	Waveguide Filter	No
Marquardt and Muller (1977)	1977	Waveguide Filter	No
Marshall and Tissi (1991)	1991	Waveguide Filter	No
Harscher et al. (2000)	2000	Coaxial Filter	No
Harscher and Vahldieck (2001)	2001	Coaxial and Waveguide Filter	No
Harscher et al. (2001a)	2001	Coaxial Filter	No
Harscher et al. (2001b)	2001	Coaxial Filter	Yes
Pepe et al. (2005)	2005	Waveguide Filter	Yes
Meng and Wu (2009a)	2009	3 Waveguide Filters	Yes
Li et al. (2019)	2019	Waveguide Filter	No

A short summary of the sensitivity analysis-based filter tuning methods is presented in Table 4 which shows the filter topology on which each method was validated. The table also depicts if a particular strategy was used for tuning cross-coupled filters or not.

5) Soft Computing-based Methods for Filter Tuning
   a) Heuristic Methods for Filter Tuning
      1. **Derivative-Free Methods** (Cegielski and Michalski, 2008): The authors developed a filter tuning approach combining Simulated Annealing (SA) (Kirkpatrick et al., 1983) for pre-tuning and Direct Search (DS) (Lewis et al., 2000) for fine-tuning, using tuning screw positions as independent variables during optimization. They employed the Intelligent Automatic Filter Tuning Tool (IAFTT) (Intelligent Automatic Filter Tuning Tool, 2007) for experiments. Such a method avoided the efforts in modelling and measurements. However, the method had limitations, as it only considered the input reflection characteristics (S_{11} parameter) for tuning and required many repeated screw adjustments which can lead to inclusion of PIM effects. The other issues in this methodology were: use of two optimization routines increased the overall timing, and using results of first optimization routine in the second stage of optimization brought inaccuracies since the results rely on the initial values.
   b) Fuzzy Logic

Due to highly nonlinear relationship between tuning screws and frequency response of filters, the filter tuning process cannot be written into computer program using conventional logic statements. As a result, researchers have turned to Fuzzy Logic (FL) as it allows the possibility of integrating objective knowledge with subjective knowledge. In FL, numerical data are translated into 'Linguistic Rules' using a membership function and the defined if-else statements assist in decision making process using the membership function value obtained. This approach aligns with how industry technicians traditionally use set theory to adjust filter couplings based on their expertise and visual inspection of measurement data.

The initial adoption of FL for filter tuning stemmed from its ability to merge measured data, theoretical models, and expert knowledge into a cohesive framework. Researchers have explored FL for tuning active filters 1994 (Moreira-Tamayo et al., 1994). However, considering the scope of this literature review, the efforts to tune MW passive filters are discussed in the following sub-sections.

(1) Filter Tuning using Conventional Fuzzy Logic
   A. Filter tuning without considering experience of tuning expert

In filter tuning using FL without incorporating human experience, the input given to the model are the S-parameters at predefined frequency points. The output of this model is the tuning variables that help derive the CM. By comparing the generated CM with an ideal CM, the tuning elements responsible for detuning are identified.

1. **Methods Based on Mamdani-Type Fuzzy Inference System** (Miraftab and Mansour, 2002a) and (Miraftab and Mansour, 2002b): These methods employed Mamdani-type Fuzzy Inference System (FIS) to tune MW filters. In this approach, the S-parameters served as linguistic antecedents, while the coupling elements were the linguistic consequences. The system used triangular membership functions for the input/output fuzzy sets. Training pairs facilitated CM extraction and the identification of detuned tuning elements. However, this approach had several drawbacks:
   - It did not specify the amount of adjustment needed.
   - It required substantial data pairs before building the FL system.
   - Two separate FLSs were used for different severity of detuning i.e. slightly detuned or highly detuned.
   - It struggled with higher-order and cross-coupled filters.
2. **Method Based on Sugeno-Type Fuzzy Inference System** (Miraftab and Mansour, 2004): This method utilizes a single Sugeno-type FIS for dealing with slightly detuned and highly detuned problems. Gaussian membership functions were applied, and use of subtractive clustering (Chiu, 1994) minimized the number of fuzzy rules, with each cluster defining a rule. This approach could generate the CM from the S-parameters at the predefined frequency sampling points and identified detuning causing elements. Despite these advances, the method faced limitations:
   - It required the establishment of complex fuzzy logic rules.
   - It was not fully effective in achieving precise tuning.

Other than the limitations pointed above for methods presented in (Miraftab and Mansour, 2002a), (Miraftab and Mansour, 2002b) and (Miraftab and Mansour, 2004), a common limitation of all these methods was that the experience of tuning experts was not taken into consideration. This reduced the accuracy of the system, making them unsuitable for commercial filter tuning applications.

B. Filter tuning considering experience of tuning expert

The intuitive decision-making of human experts while tuning the filters has been incorporated into FL-based filter tuning systems, aiming to enhance the effectiveness of this methodology in tuning the filters. The following methods present the research works in which human insights were combined with FL to create more intelligent and efficient tuning algorithms.

1. **Method Based on First-Order Sugeno-type FIS** (Miraftab and Mansour, 2005)**:** This study introduced a filter tuning algorithm using human expert knowledge embedded in a Fuzzy Logic Controller. The first-order Sugeno-type FIS employed Gaussian membership functions and variable standard deviations. Data were grouped using Subtractive Clustering (Chiu, 1994) and the elements of CM provided information about the tuning screws causing detuning of the filter. But the method was limited by its reliance on the S_{11} parameter and its application to simple lossless filters only.
2. **Two-Step Method** (Miraftab and Mansour, 2006)**:** This approach used a two-step tuning routine – Coarse and Fine tuning, each with separate fuzzy controllers. The experience of filter tuning expert was directly added as linguistic 'if-then' rules in this research work. Triangular membership functions were used. This method aimed to automate the tuning process and improve accuracy using CM but remained restricted to lossless filters designed with in-line configuration.
3. **Fully** Automated **Tuning Method** (Miraftab and Mansour, 2008)**:** Building on (Miraftab and Mansour, 2006), this publication presented a fully automated filter tuning system based on FL which could handle complex filter topologies This method also used triangular membership functions. The method emphasized the necessity of extracting the CM to achieve accurate filter tuning. Despite advancements, this method also faced limitations such as inability to address resonator loss and was confined to in-line filter configurations. This method also struggled with extracting filter parameters and was not practical for industrial applications.

(2) Variable Fuzzy Logic

To address the challenges associated with defining crisp fuzzy rules, variable FL systems were used to enhance filter tuning accuracy. The following research works were conducted in this domain.

1. **Variable Universe Adaptive Fuzzy Logic** (Peng et al., 2021)**:** The accuracy of traditional FLS depends on the number of cases used to

define fuzzy rules. To address this issue, a variable universe adaptive FLS was introduced to contract or expand the universe based on the tuning requirements. This helps in achieving more reliable tuning. However, this approach requires sequential and progressive adjustment of each tuning screw, which can lead to error propagation throughout the tuning process.

2. **Dynamic Attention Based Fuzzy Logic** (Bi et al., 2022)**:** This study introduced an advanced FLS with dynamic attention capabilities to ensure the real-time adaptation of tuning goals and the evaluation function time without altering the existing fuzzy rules. It offers a quick, precise and efficient method for tuning complex filters. Despite its advantages, this approach has limitations, including a lack of capability for autonomous learning of tuning procedures and adjustments to critical parameters during optimization.

FL methods allow us to express coupling strength with the help of membership function and can assist in tuning the filter without fetching the specific coupling matrix values. However, for achieving accurate results, it requires defining decent number of linguistic rules which consequently brings in more complex computations and, consequently, more delay. To improve the robustness and efficiency of filter tuning by adapting to real-time changes and reducing dependency on predefined fuzzy rules, dynamic fuzzy methods were presented. However, these methods also failed to optimize the parameters and faced challenges due to error propagation.

c) Machine Learning-based Filter Tuning

(1) Unsupervised Learning

1. **Clustering Method** (Mirzai et al., 1989): Researchers explored ML for tuning waveguide filters by leveraging pattern recognition and adaptive signal processing. Initial tuning was conducted manually, with fine-tuning performed using adaptive combiners using polar plot which is set to depict the value of input reflection parameter. Data from well-tuned and intentionally detuned filters was input into a Recursive Least Squares (RLS) algorithm. This dataset consisted of information about features to be learnt by ML algorithm and the level of detuning. The designed algorithm estimated the necessary adjustments to minimize MSE by indicating the tuning element to adjust and the required adjustment amount. The algorithm adjusted tuning elements based on the maximum error value from each iteration. This method was robust and adaptable, even for tuning the group delay. However, it had several limitations: the tuning was ultimately performed by a human operator, details about calibrations and manipulations were not mentioned, only resonators were considered in this work, and the coupling screws were pre-set, ignored certain tolerances, and thus was applicable to fine-tuning. Additionally, the ML algorithms require a large amount of accurate training data for efficient and consistent performance. This increases the computation burden and computation time of the process. Also, the ML algorithm is usually biased towards the specific equipment used to collect the training samples.

(2) Supervised Learning

(a) Inverse Filter Model based on Artificial Neural Networks (ANN)

With the increased computational capacity of systems, Artificial Neural Networks (ANNs) were started to be considered among the most reliable tools to come-up with multidimensional universal approximators. They have the capacity to determine the underlying patterns in the complicated devices without knowing their working principle. In terms of MW filter tuning, ANNs had the potential to create a precise mapping between S-parameters and tuning screw deviations, resulting in an effective inverse black-box model. By training ANNs with samples from a well-tuned filter or a 'golden filter,' they can learn to predict tuning screw errors from raw S-parameters. This trained model can then allow for accurate adjustments to achieve desired filter characteristics. Generalization Error (GE) of the trained model, which provides information about how well the model performs on the test data not seen during training, was needed to be minimized to ensure better tuning ability of the algorithm. Various efforts put forward to design ANN-based filter tuning algorithms are as under:

In 2010, the idea of using ANN for MW filter tuning was first reported (Michalski, 2010a). An inverse model linking S_{11} parameters to tuning screw deviations using Back Propagation was introduced. The network architecture with a Feed-Forward (FF) structure with one hidden layer was selected. The samples for collecting the training data for the inverse model were collected randomly. This model analyzed its generalization by testing it with filters of the same topology but trained on data from different filters. Although the ANN could simultaneously determine the necessary tuning for all elements, the algorithm was basic, requiring fine-tuning and lacking analysis on optimal ANN structure.

The work in (Michalski, 2010b) expanded on (Michalski, 2010a) by incorporating multiple golden filters, which improved the quality of training vectors and reduced GE. However, this method had limitations: the real-time upgradation of tuning model was not possible, the tuning model could only deal with a specific filter version, only cavity tuning was addressed (with couplings pre-tuned), and yet, again the analysis about correct ANN architecture was not studied.

Further extending this work (Michalski et al., 2011), analyzed ANN structure for filter tuning, also determining the optimal number of frequency sampling points and input neurons for selected was presented. This analysis reduced the ANN's weights, GE, and learning time. Yet, the method still assumed pre-tuned inter-resonator couplings and only addressed cavity screw tuning, limiting its commercial applicability.

The use of Principal Component Analysis (PCA) in ANN-based filter tuning was introduced in (Kacmajor and Michalski, 2011a) which truncated the data points which had less influence. This assisted in reducing input vector dimensions while maintaining ANN performance. Additionally (Michalski and Kacmajor, 2011), applied Wavelets, specifically the Daubechies Wavelet (D4), to compress S-parameters and speed-up ANN training i.e., it reduced the number of neurons in ANN structure. However, Wavelet techniques were limited to simple ANN structures and did not handle cross-coupled and higher-order filters.

1. **Inverse Model for Tuning Fixed-Band Filter** (Michalski, 2011): In 2011, the research efforts presented in (Michalski, 2010a) and (Michalski, 2010b) for using ANNs for MW filter tuning were combined to propose a sequential filter tuning process using S_{11} parameters of filter as the tuning criteria. Although this advancement opened the path to exploring ANNs for automating the filter tuning process, this solution was solely dependent on the quantity and quality of training dataset in addition to being reliant on the specific filter version only.
2. **Inverse Model for Tuning Variable-Band Filter** (Kacmajor et al., 2014): The authors of this work proposed an inverse model to tune variable frequency filters and showed that after the frequency shift, the working signal must undergo a phase transformation. Despite improving generalization, the method was limited to S_{11} parameters and could not fully automate filter tuning.
3. **Hyperparameter Tuned Automatic Filter Tuning** (Boyer De La Giroday, 2016): The work presented in (Michalski, 2010a) and (Michalski, 2011) was then further explored in which the effect of changing hyperparameters and activation functions for automating the filter tuning process. An all-pole filter without cross-couplings were used by the author to validate the methodology. However, the authors concluded that the generalization error was still not enough to tune the filters efficiently compared to tuning experts.

ANNs ability to model complex relationships and interactions for

complex processes makes them most suitable tool for multi-dimensional approximation in tuning of MW devices and research in this field is still on-going. However, there are several key issues with this approach.

- A large amount of training data is necessary.
- Generalization is not achievable.
- If the current data falls outside the training data boundaries, the optimal solution cannot be obtained.
- Real-time updates to the tuning model are not possible.
- The training model may suffer from overfitting due to the back-propagation method and initial weight choices.
- The training phase is time-consuming.

(b) Support Vectors

Support vectors Regression (SVR) is valued for their effectiveness with small sample sizes and its ability to avoid falling into local minima, distinguishing it from Neural Networks (NNs). This capability makes SVR advantageous for filter tuning applications. Many research scholars have worked towards finding a solution to filter tuning problems using this approach. Various publications discussing filter tuning using support vectors are as follows.

1. **Method with Least Squares Support Vector Regression** (Han et al., 2010)**:** The first application of SVR in filter tuning utilized a wavelet kernel mechanism with Least Squares Support Vector Regression (LS-SVR). This approach was used to model the relationship between tuning screw adjustments and coupling changes (presented via coupling matrix). However, screw positions were approximated by solving optimization problems instead of being measured directly from the filter under consideration when led to inclusion of inaccuracies in the outcomes. Additionally, this method was restricted to simple filter topologies.
2. **Method with Multi-Kernel Least Squares Support Vector Regression** (Zhou and Huang, 2013)**:** To address the limitations offered by LS-SVR algorithm in tuning the filters and to deal with multiple output MW filters, researchers introduced Multi-output LS-SVR (MLS-SVR) techniques. For example, a Multi-Kernel Linear Programming Support Vector Regression (MKLP-SVR) was used to develop an efficient electromagnetic (EM) coupling model for tuning the filters in this method. For this, the method presented in (Han et al., 2010) was used as a basis, and data about the positive or negative outcome of the filter tuning process was collected when a tuning expert tuned the commercial filters. This model could map the S-parameters of a filter to a corresponding CM (Hong and Lancaster, 2001) to come up with an intelligent filter tuning method and demonstrate its effectiveness with moderate-order cross-coupled filters. The main limitation of this research was its reliance on costly optimization routines to determine the necessary deviations for tuning the filters.
3. **Methods with Linear Programming Support Vector Regression** (Zhou et al., 2013) and (Zhou et al., 2015)**:** A hybrid filter modelling approach incorporating Multi-Kernal with Prior Knowledge into Linear Programming Support Vector Regression (MKPLP-SVR) was proposed in 2013 (Zhou et al., 2013). The training data was collected during the tuning process. While this method showed promise with electrically tunable filters, it struggled with highly detuned states and lacked detailed model and hyperparameter selection criteria. Later, a refined MKPLP-SVR model (Zhou et al., 2015) used two complementary models - an empirical coarse model and an SVR model. The use of prior knowledge enhanced the accuracy and extrapolation capacity of the proposed model. This method was again tested on an electrically tunable filter still faced challenges with highly detuned filters and provided S-parameters only in terms of coupling models as in previously published works published in this category i.e. (Han et al., 2010), (Zhou and Huang, 2013), and (Zhou et al., 2013).
4. **Method with Pole-Residue Based Multi-Kernel Least Squares Support Vector Regression** (Cao et al., 2018b)**:** This methodology addressed highly detuned filters by using a pole-residue-based MLS-SVR approach (Xu et al., 2013). This model relied on pole and residue information of the Y-parameters (being more accurate than other rational coefficients) rather than raw S-parameters. For converting S-parameters to Y-parameters, the method presented in (Gustavsen, 2006) was used. This method exhibited improved accuracy than other previously published research works discussed above but was limited to simpler filter topologies and was constrained by the general inaccuracy of physics-based simulation data.

The Support Vector models developed by researchers to address the filter tuning problem are indirect; S-parameters are represented by a Coupling Matrix (CM) rather than their original form obtained from a VNA. Additionally, errors arise from approximating screw positions based on optimization problem solutions and modelling only the filter structure but not the experience of tuning experts.

(3) Reinforcement Learning

Reinforcement Learning (RL) models, inspired by animal learning processes, use rewards to optimize decision-making. The process of reinforcement learning is inherently a temporal difference approach that is expressed mathematically in (Sutton and Barto, 1998). This mathematical framework was later expanded upon in (Watkins, 1989) and became known as Q-learning. In RL, an agent explores an environment, receiving rewards or penalties based on actions, to maximize future rewards/to learn the optimal policy. The key studies carried out in this field are as under.

1. **Deep Q-Learning** (Wang et al., 2015b): The application of this nature-inspired learning approach (i.e., RL) for modelling the filter tuning process was introduced in 2015, inspired by the results from DeepMind (Mnih et al., 2015). DeepMind's algorithm, a modified version of (Mnih et al., 2013), outperformed human experts in playing Atari games. In (Wang et al., 2015b), the authors used a Back Propagation Neural Network (BPNN) for training a 20-20-4 FF simulated Network (which acted as a Deep Q-Network (DQN) in that research work). PCA was employed before training to reduce the input data dimensionality. The authors tested their algorithm on a filter (a part of commercial combiner) by tuning only two screws mounted directly over the resonators. The study faced limitations such as only considering S_{11} parameters, a poorly defined reward strategy, and solution often trapping into local minima.
2. **Deep-Deterministic Policy Gradient** (Wang et al., 2018) and (Larsson, 2018): For tuning the filters in continuous action space, this method used Deep-Deterministic Policy Gradient (DDPG) and included a controlled Vector Field (Wang et al., 2016) (obtained initially by independently tuning the screws). This allowed achieving a better reward function and enhanced generalization abilities. However, the work was constrained to S_{11} characteristics only and faced challenges in step size and curve truncation decisions in the considered vector field.
3. **Optimal Deep-Q-Learning** (Sekhri et al., 2019): This method improved on (Wang et al., 2015b) with a Lagrangian multiplier in DQN to find global minima. This involved using a Convolutional Neural Network (CNN) for better performance, though it still faced issues with limited S_{11} data and reward strategy.
4. **Double Deep-Q Learning** (Sekhri et al., 2020): Double Deep Q-Learning (DDQN) approach for filter tuning, which avoided the maximization bias problem offered by conventional Deep-Q-Learning. For reducing the dimensions of data, Locally Linear Embedding (LLE) technique (Roweis and Saul, 2000) was used. This method was efficient in comparison to other similar

methods but was again limited to input port's reflection parameters only.

5. **Deep Imitation-Reinforcement Learning** (Lindstah and Lan, 2020) and (Lindståhl, 2019)**:** Different from other methods presented above in this category (i.e. RL-based Filter Tuning), the authors combined S_{11} and S_{12} parameters for tuning the filter. The method worked with a discrete reward function defined in (Wang et al., 2015b) using DDPG algorithm presented in (Wang et al., 2018) but it required much more data-points as compared to other methods discussed above.
6. **Continuous Reinforcement Learning** (Wang and Ou, 2022): A continuous RL algorithm with human-inspired reward functions was introduced. A robotic system was used to collect training data from single channel of a commercial combiner unit. Authors made comparisons in terms of total tuning time and tuning performance between several reward functions and concluded that the human behavior inspired reward function improved performance of the system. But this method relied on a simple model and could only track vertical curve changes, thus restricting it for its use in tuning commercial filters.
7. **Model-Based Reinforcement Learning** (Nimara et al., 2023): Different than other model-free methods presented above, this method used a model-based approach to solve the complex problem. The authors considered a big hurdle i.e. transferring of the learned knowledge, but the approach was very basic. The authors designed a better reward function as compared to all other RL-based methods mentioned in this paper, but this methodology was capable of simple filters only.

The RL-based methods presented above in this category showcase the evolution and challenges of applying RL to filter tuning. While this method was used to tune the filters in a simulated environment, the common issues with RL are.

- An exponential increase in the time delay when too many layers are used.
- Unavoidable need for a time-consuming training phase.
- High computational power is essential for RL, as agents require an immense number of states to learn accurate strategies.
- Biasness is generally introduced in reinforcement learning algorithms when an agent fails to thoroughly explore the environment.
- The choice of reward function significantly impacts the final outcome, and the lack of standardized instructions for deciding rewards can lead to inaccuracies.

d) Filter Tuning based on Neuro-Fuzzy System

A combination of FL (Sugeno-type FIS) with Neural Networks (NNs), a hybrid approach to come-up with a universal approximator was validated for various applications (Jang, 1993). This system leverages NNs to determine the parameters of the Fuzzy Logic System (FLS), offering advantages such as online learning, rapid processing, low computational complexity, fast learning, and reduced errors.

1. Method in (Kacmajor and Michalski, 2011b): An adaptive network-based fuzzy inference system (ANFIS) was used for mapping the filter's S-parameters to tuning screw deviations. This method used the same approach as in (Jang, 1993) and was built on the efforts of Michalski (2010a) to introduce a new multi-dimensional approximator for filter tuning. This approach required fewer learning vectors and achieved lower Learning Error (LE) and Generalization Error (GE) compared to the ANN-only method described in (Michalski, 2010a). However, using Neuro-Fuzzy System (NFS) for filter tuning was limited by the following factors – this method was restricted to reflection coefficients (S_{11}) only (as it assumed that the couplings were pre-tuned), the time elapsed in the training process was high, the data needed to be pre-processed, the low convergence rate of the parameters, and there were problems associated with updating the model in real-time. All these factors seized the possibility of using this method in industrial filter tuning applications.

e) Linear Mapping-based Filter Tuning

The use of Linear Mapping was explored by researchers in 2012 to correlate variations in S-parameters with changes in height of tuning screws. The details of the only method proposed to tune MW filters with this approach is as follows.

1. **Linear Matrix Operator-Based Method** (Michalski, 2012)**:** Another filter tuning approach was proposed, which used linear mapping instead of traditional data-driven models. IAFTT Robot (““Intelligent Automatic Filter Tuning Tool, 2007;) was used to collect samples. The linear matrix was computed using the Least-Squares Method (LSM) (Wolberg, 2006), and outlier elimination was applied to improve approximation accuracy. Principal Component Analysis (PCA) was used to reduce dimensionality and accelerate the tuning process. Unlike ANN-based methods, this approach did not require extensive training, making it faster. However, its limitations include random dataset collection, focus only on cavity tuning within a limited range, pre-tuning of couplings (EM coupling between adjacent and non-adjacent resonators) and excluding them while dataset collection, which made it unsuitable for tuning raw filters.

While the training stage is not required for implementing Linear mapping-based filter tuning methodology, the performance of this strategy heavily depends on the volume and quality of the data collected.

f) Tuning Filters via Linear Decomposition of Reflection Parameters

The core concept behind using this technique for filter tuning was the assumption that the relation between filter scattering parameters and tuning elements can be represented by functions composed polynomials sums. The filter tuning methods based on this methodology are as under:

1. Methods Based on Linear Decomposition of S-Parameters (Tomasz and Julian, 2012) and (Kacmajor and Michalski, 2013): In (Tomasz and Julian, 2012), a Linear Decomposition technique was proposed for filter tuning, which removed the key limitations of ANN-based and Linear Matrix Operator methods. This approach eliminated the need for random detuning and extensive data pairs by using coarse data collected in a controlled manner. Only one screw was adjusted at a time while extracting data pairs. The study focused on tuning only cavity screws at a time, with limitations including consideration of only the S_{11} parameter and applicability to slightly detuned filters only. Building on this (Kacmajor and Michalski, 2013), expanded the method presented in (Tomasz and Julian, 2012) to include both reflection and transmission characteristics, making it more applicable to real-world scenarios. Although it used a similar data collection process and polynomial-based model, it improved upon (Tomasz and Julian, 2012) by incorporating cross-couplings. Despite its speed advantage over CM Extraction-based filter tuning methods, the optimizer's response was slower than ANN-based approaches for finding precise screw deviations.

This methodology eliminated the training phase but needed optimizations to provide the amount of tuning needed, making this process time-consuming.

A short summary of the soft computing-based filter tuning methods is presented in Table 5 which shows the filter topology on which each method was validated. The table also depicts if a particular strategy was used for tuning cross-coupled filters or not.

6) Blended Methods for Tuning the Filters

Several authors have explored filter tuning through blended

Table 5
Summary of various soft computing based filter tuning techniques described in this review.

Soft Computing Technique	Reference Number	Year of Publication	Type of Filter used for Validation	Tuning cross-coupled filters
Heuristic Methods	Cegielski and Michalski (2008)	2008	Coaxial Filter	No
Fuzzy Logic	Miraftab and Mansour (2002a)	2002	Not Mentioned	No
	Miraftab and Mansour (2002b)	2002	Not Mentioned	No
	Miraftab and Mansour (2004)	2004	Not Mentioned	Yes
	Miraftab and Mansour (2005)	2005	Not Mentioned	No
	Miraftab and Mansour (2006)	2006	Waveguide Filter	No
	Miraftab and Mansour (2008)	2008	Waveguide Filter	No
	Peng et al. (2021)	2021	Inline Coaxial Filter	No
	Bi et al. (2022)	2022	Inline Coaxial Filter	No
Neuro-Fuzzy System	Kacmajor and Michalski (2011b)	2011	Coaxial Filter (Duplexer)	Yes
Machine Learning	Mirzai et al. (1989)	1989	Waveguide Filter	No
	Han et al. (2010)	2010	Waveguide Filter	No
	Zhou and Huang (2013)	2013	Combline Filter	Yes
	Zhou et al. (2013)	2013	Waveguide Filter	Yes
	Zhou et al. (2015)	2015	Waveguide Filter	No
	Cao et al. (2018b)	2018	Coaxial Filter	No
	Michalski (2011)	2011	Coaxial Filter (Duplexer)	Yes
	Kacmajor et al. (2014)	2014	Not Mentioned	No
	Boyer De La Giroday (2016)	2016	Coaxial Filter	No
	Wang et al. (2015b)	2015	Coaxial Filter	No
	Sekhri et al. (2019)	2019	Combline Filter	No
	Wang et al. (2018)	2018	Coaxial Filter	No
	Larsson (2018)	2018	Coaxial Filter	No
	Sekhri et al. (2020)	2020	Combline Filter	No
	Lindstah and Lan (2020)	2020	Coaxial Filter	No
	Lindståhl (2019)	2020	Coaxial Filter	No
	Wang and Ou (2022)	2022	Coaxial Filter	No
	Nimara et al. (2023)	2023	Combline	No
Linear Mapping Technique	Kacmajor and Michalski (2013)	2012	Coaxial Filter (Diplexer)	Yes
Linearly Decomposing Reflected Characteristics at Input Port	Tomasz and Julian (2012)	2012	Coaxial Filter (Duplexer)	No
	Kacmajor and Michalski (2013)	2013	Coaxial Filter (Duplexer)	Yes

approaches that combine two or more methodologies together to enhance accuracy and efficiency. Theoretically, these combined methods are expected to yield superior results compared to those achieved with single-method approaches. This section highlights relevant publications that have employed such amalgamated techniques.

1. **Combining Vector Fitting and Aggressive Space Mapping** (Zhang et al., 2013a): The authors proposed a filter tuning method that integrated Vector Field (VF) method with the Aggressive Space Mapping (ASM) method. The VF method was used for diagnosing filter parameters from a generalized equivalent circuit model as Y-parameters, while the ASM technique determined the optimal screw positions and their correct tuning directions. Although this approach was validated on higher-order filters, this approach was slow due to the high number of sample points required for achieving higher accuracy. Also, this methodology did not consider asymmetrical phase shift effects.
2. **Combining Cauchy Method and Aggressive Space Mapping** (Zhang et al., 2013b) and (Zhang and Yan, 2015): These studies used a combination of the Cauchy method with ASM approach for proposing a filter tuning method. In these methods, S-parameters were converted into rational functions using Cauchy method to extract the coupling matrix, and an ASM model (optimized) then determined screw adjustment directions. The methodology presented in (Zhang et al., 2013b) needed sampled frequency points close to the passband and required iterative adjustments. The method in (Zhang and Yan, 2015) removed asymmetrical phase shifts before applying the Cauchy Method, addressing an aspect not covered in (Zhang et al., 2013b). Overall, this blended methodology was limited to lower-order filters with either no cross-coupling or just a few of them.
3. **Combining Cauchy Method and Implicit Space Mapping** (Wu et al., 2017): This method combined human experience with an Implicit Space Mapping (ISM)-based data optimization technique. Initial coarse tuning was done manually to handle large deviations, followed by fine-tuning using the ISM algorithm. The idea behind implementing this method was that the tuning experts usually take a long time to fine tune the filter after filter pre-tuning is done. The coupling values obtained from the Cauchy method were used as inputs to the algorithm, with phase and loss effects removed using Genetic Algorithm (GA). Despite its advantages, this method assumed the resonators to have uniform Q_{ul}, which is not true for the commercial filters.
4. **Combining Cauchy Method, Neural Network, and Implicit Space Mapping** (Wu et al., 2018a): The coarse tuning process for severely

detuned filters used information about poles and zeros of the input reflection parameters, and iterative optimization techniques improved their phase. This method utilized standard transformations defined in (Esmaeili and Borji, 2010) to convert S-parameters to Y-parameters and then used Cauchy method defined in (Wang et al., 2015a) for extracting the coupling matrix (CM) elements in the fine-tuning stage, aiming to minimize residual errors. To obtain the Y-matrix, partial expansion method presented in (Cameron, 2003) was employed. A complex neural network model, trained with the Gradient-Descent method, established the mapping between ideal and actual models using ISM. This approach provided precise tuning adjustments required for each tuning screw using (Cheng et al., 2015), though it was restricted to coaxial filters and required additional rotation transformations for the CM.

5. **Combining Vector Fitting, Fuzzy Neural Network, and Improved Space Mapping** (Wu et al., 2018b): This tuning method involved two stages: initial tuning and fine tuning. The Quantum Greed Algorithm (Yang et al., 2014) was employed to avoid local minima issues, followed by phase shift removal and coupling matrix (CM) extraction using VF approach. The method integrated a Fuzzy Neural Network (FNN) based on the T-S (Takagi-Sugeno) model for tuning accuracy, with iterative improved SM methodology implemented on this FNN model to determine optimal screw positions.

A short summary of blended filter tuning methods is presented in Table 6 which shows the filter topology on which each method was validated. The table also depicts if a particular strategy was used for tuning cross-coupled filters or not.

This section has provided a comprehensive analysis of existing research in filter tuning. Publications published under each category are listed individually along with the year in which they were published. As much as possible, authors have tried to maintain the timeline in each category to show how a particular technique advanced with time (although, at some instances it was not possible to do so because of the information flow authors wanted to present). Additionally, the tables providing information about the type of filter units used to validate the given methodology are presented where it has also been shown if the particular methodology was capable of tuning cross-coupled, i.e. the filters that are more widely used in communication, or not.

3. Research insights

This section provides detailed research insights. Numerous publications presented by the research community are the testimony of the fact that the filter tuning is a complex task and the search to find optimal method(s) of tuning these filters is still on-going. A bunch of researchers are directing their efforts to automate this process, and they have built customized machine/tuning robots to implement their methodologies. Since this review paper is mainly dedicated to reviewing the various filter tuning techniques (but not specifically the hardware built to automate the filter tuning process), the automated filter tuning hardware solutions are not mentioned in this review. Still, for the knowledge of curious readers, none of the available solutions is able to provide full solution (hardware + software) to tune the various kinds of filters autonomously once these filters are assembled.

Table 6
Summary of various blended filter tuning techniques described in this review.

Reference Number	Year of Publication	Type of Filter used for Validation	Tuning cross-coupled filters
Zhang et al. (2013a)	2013	Coaxial Filters	Yes
Zhang et al. (2013b)	2013	Coaxial Filters	Yes
Zhang and Yan (2015)	2015	Coaxial Filter	Yes
Wu et al. (2017)	2017	Coaxial Filter	No
Wu et al. (2018a)	2018	Coaxial Filter	No
Wu et al. (2018b)	2018	Coaxial Filter	Yes

3.1. For time domain

The TD-based filter tuning methods are a special case of filter tuning and have not attracted the attention of researchers. This is evident from Fig. 1, which clearly shows that FD-based tuning methods have grabbed significant attention and that various FD-based tuning methods have been proposed. Among the five TD-based filter tuning methods presented in this study, four were introduced in 1999, while the remainder was published in 2014. No further research has been reported in the literature for TD-based filter tuning methods. This is due to the fact that the TD-based filter tuning methods have following issues.

- Cross-coupling values were set lower than the main-line coupling.
- A 'golden filter unit' was required to obtain an ideal response, which limited its applicability.
- Human intervention was needed for the actual tuning of the filter.
- Exact values for coupling and resonant frequency were challenging to determine, necessitating fine-tuning.
- The method struggled with tuning the filters with asymmetrical frequency responses.
- Multiple screw adjustments could induce Passive Intermodulation (PIM) effects and damage the filter.
- Sequential tuning was required, starting from outer screws and moving inward to the center screw (or screws).

Considering these limitations, the time domain-based tuning category has not been considered in this section. Rather, the efforts have been made to draw insights from the trends seen in the area of frequency domain only.

3.2. For frequency domain

The applicability, limitations and research insights of various filter tuning techniques proposed by research community in frequency domain are listed in Table 7.

Next, Fig. 3 illustrates research trends over a ten-year span. Since the first short-circuiting-based method was reported in 1951 and the first filter tuning method based on sensitivity analysis can be traced back to mid-1970s, the division of years is chosen accordingly. The number of publications in each 10-year span can be seen in horizontal grey row, while the total number of publications in each category are shown in the vertical grey column. The number written in each colored block indicates the number of publications in that respective category over a 10-year span, with each color representing a different category.

The analysis of Fig. 3 reveals a marked interest in several key areas, including blended methods, space mapping, soft computing, sensitivity analysis, short-circuiting, and coupling matrix approaches. Overall, there is a rising trend in the research interest towards finding new ways to tune the MW filters.

Historical trends shown in Fig. 3 indicate that certain categories, such as coupling matrix methods, saw an early emergence around mid-1970s, achieving peak popularity between 2005 and 2014, before experiencing a noticeable decline. The reason for this downfall can be drawn from drawbacks of this approach enlisted in Table 7. Conversely, soft computing-based filter tuning methods, which began gaining traction in 1989, continue to be an area of active research and development. Methods based on short-circuiting and sensitivity analysis have been a constant choice of researchers. Comparing these two categories shows that short-circuiting gained momentum from researchers instead of sensitivity analysis-based filter tuning methods with a total of 13 and 11 publications, respectively. A deeper analysis of both these categories

Table 7
The key limitations of various frequency domain techniques considered in this review.

Tuning Technique	Applicability	Limitations	Research Insights
Short Circuiting Based Filter Tuning	Mainly used in: • Waveguide • Combline • Coaxial filters	• Cumulative error propagation • Require fine tuning • Shorting or strongly de-tuning the resonators is mandatory	• Simplifies the task but requires careful error management • Group delay and phase plots are effective in identifying tuning points, especially for combline and coaxial filters
Coupling Matrix Extraction Based Filter Tuning	Can deal with ride range of filter types: • Waveguide • Combline • Coaxial filters • Dielectric Resonator Filters • Microstrip Filters	• Mathematical models used are often approximations • Do not account for performance degradation due to material variations and practical uncertainties • Changing one element can affect others unpredictably	• Versatility across filter types • Enhanced Accuracy and Control • Limitations in model fidelity • It requires combining it with optimization techniques for robustness.
Sensitivity Analysis Based Filter Tuning	Primarily used in simulation of simple to waveguide and coaxial filters	•Requires repeated sensitivity measurements •Simulated linear models do not capture real filters •Does not account for mechanical adjustments affecting neighboring elements	•Systematic approach to understanding how small parameter changes affect filter performance •Practical implementation is limited due to model simplifications and lack of real-world validation
Space Mapping Based Filter Tuning	Mainly used for low-ordered: • Waveguide filters • Inline filters.	• Accuracy depends heavily on the quality of the fine model and the parameter extraction (PE) process • Mapping quality is sensitive to the chosen PE method, which is often not well-documented. • Requires many pre-assigned parameters, which can hinder convergence or cause algorithm failure.	• This technique offers a computationally efficient approach by leveraging surrogate models. • Effective in reducing EM simulation costs while maintaining acceptable accuracy • Effective in reducing EM simulations while maintaining acceptable accuracy
Soft Computing Based Filter Tuning	• Applied to a wide range of filters: coaxial, waveguide, combline, and duplexer filters. • Only the methods based on ANNs and FL are suitable for cross-coupled filters, though often with constraints	• High dependency on data quality and volume • Missing or scattered data severely affects performance • Generalization issues: models trained on one filter topology often cannot be reused for others • ANNs need large training datasets, suffer from overfitting, and cannot adapt in real-time. • Reinforcement learning introduces delay due to deep network layers	• Soft computing enables adaptive and intelligent tuning, especially when integrated with optimization or hybrid models • ANNs are limited by training scope and real-time adaptability • Linear mapping and decomposition techniques reduce training needs but rely on optimization for final tuning
Blended Methods based Filter Tuning	• Applied primarily to coaxial filters • Very limited capability of dealing with cross-coupled filters	• Combining methods introduces cumulative limitations of each individual technique • Increased computational complexity and implementation overhead • Most blended approaches rely on approximate models, which may reduce accuracy	• Combinations like Vector Fitting + Aggressive Space Mapping and Cauchy + Neural Networks + ISM have shown promise in improving tuning precision • Improved Space Mapping with Fuzzy Neural Networks enhances adaptability and convergence

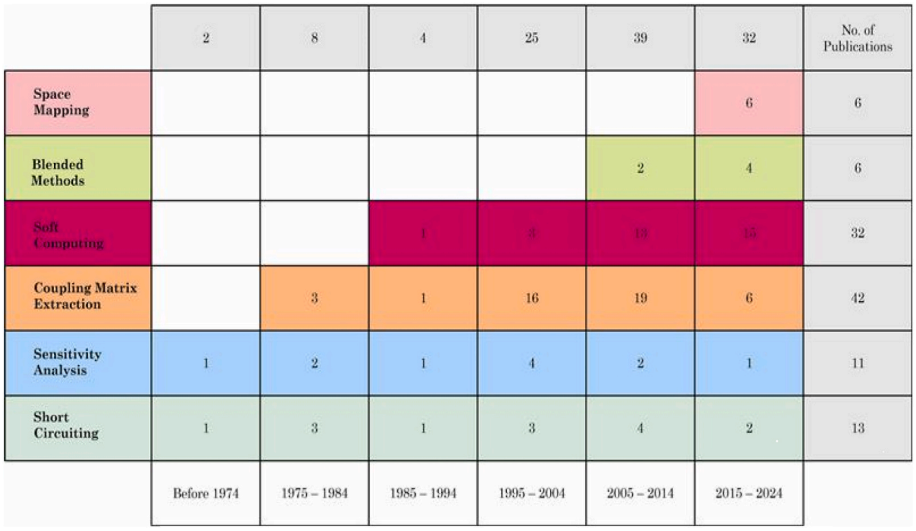

Fig. 3. Distribution of Frequency Domain-based Filter Tuning Techniques Considered in this Review.

shown in Fig. 3 tells that short-circuiting based filter technology has experienced more growth than sensitivity analysis in last 20 years. This is because of the fact that short-circuiting-based sequential methods can break a bigger problem into smaller chunks, thus having the potential to solve this complex filter tuning problem.

Considering recent developments in this field, it can be seen that in the last 10 years i.e., between 2015 and 2024, a total of 32 publications are reported, suggesting a shift in research focus within the field. It also emerged from Fig. 3 that the filter tuning methods based on 'Soft Computing' have the greatest number of publications, i.e. 15 in the last 10 years. This can be attributed to the fact that the computation capacity has increased manifolds recently with the introduction of powerful CPUs and GPUs. This increased computation power further led to evolution of several fast and efficient algorithms. In addition, we can see that a new category, 'Space Mapping' made its way into filter tuning applications in this span. Also, the latest advancements highlight progress in blended filter tuning methods. This 'Blended Methods' category for filter tuning emerged in the year 2013 and is gaining popularity recently.

Thus, the trends evident in Fig. 3 indicate that the efforts to find new efficient filter tuning algorithm(s) are growing with each passing decade, and the insights from Table 7 reveal that each category of filter tuning exhibits its own limitations. Hence there is a need to devise a novel approach that can use combination of signal processing and image processing techniques to solve the complex problem of tuning the filters efficiently and/or autonomously.

The literature review revealed the absence of an Artificial Intelligence (AI) and Machine Learning (ML)-based algorithm for filter tuning applications. Such method can be implemented using soft computing-based method with which the authors have previous experience (Sekhri et al., 2019) (Sekhri et al., 2020). The following section details the implementation of this technique for efficient filter tuning.

4. DSmT and ML-based filter tuning algorithm

Fig. 4 presents a novel filter tuning algorithm in which a combination of theoretical knowledge of filter design and the analysis of tuning expert's experience was used for filter tuning. In expert-based systems, the experts can also help in determining the relevance of criteria by ranking comparison (Więckowski et al., 2023). However, in our work, the expert was used to come-up with an intelligent tuning strategy. Human Activity Recognition (HAR) has recently gained interest in the research community. State-of-the-art and research challenges in HAR for multi-sensor information fusion have been researched (Qiu et al., 2022) and multi-modal approach for tracking human gestures has been evaluated by Samee Ullah Khan et al. (2025).

A 5-pole in-line filter having solid cylindrical resonators was considered to test the proposed algorithm. To make the system knowledge-based, Markov chains were used. The theoretical knowledge from filter design parameters was used to predict S-Parameter variation using Markov Chain model. Two cameras were used to record the videos when tuning expert tuned the filter. The first camera was placed overhead and captured rotation direction and approximated rotation angle of the customized screwdriver, and second camera was placed in the plane parallel to the Vector Network Analyzer (VNA) screen and captured the variation in S parameters (both S_{11} and S_{21}). Marker-based approach (Benmessabih et al., 2024) was used for capturing the actions of filter tuning expert. The variation in S-parameters was given to DSmT (Dezert - Smarandache Theory) algorithm (Smarandache and Dezert, 2009) which is an extended version of traditional Dempster-Shafer Theory (Blasch et al., 2013). The visual data is pre-processed, and Isometric Mapping (Isomap) method (Rassias, 1999) was used for dimensionality reduction before the improvised modified DDQN (Double Deep Q-Learning) algorithm which used Prioritized Experience Replay (Fahrmann et al., 2022) to ensure accuracy in predicting the correct screw position in a simulated environment.

The policy generated by the proposed algorithm facilitated accurate and efficient filter tuning. During implementation, a discount factor of 0.90 and a replay buffer of 200,000 were used. The maximum allowable screw turns were set to three full rotations (1080°). A CNN architecture with one hidden layer and a parametric ReLU activation function was employed.

When trained, the proposed algorithm achieved convergence within 400 training epochs, faster than the standard DDQN (~600 training epochs) as shown in Fig. 5. Training of the standard DDQN algorithm took approx. 23 h, while the proposed algorithm took approx. 28 h. The increase is due to complexity in the structure of the proposed model, and the fusion of different techniques. Once the model was trained, the real-time inference (predicting next screw turn) took <0.5 s per decision, ensuring suitability for online tuning. Also, the fusion of Markov Chain and DSmT methods assisted in reducing the redundant state evaluations and improving the computational efficiency by approximately 18–22 % when compared to standard DDQN algorithm. The results (also depicted in Fig. 6) showed that the proposed algorithm demonstrates acceptable computational efficiency for real-time filter tuning scenarios.

Fig. 7 represents the results of tuning a 5-pole coaxial filter using the proposed algorithm, where blue line represents the reflection parameter, and the black line represents the transmission parameter. The return loss target is shown in red, and the insertion loss limit is indicated by the green line. Achieving the return loss below a target line of −16 dB confirms the successful tuning of the filter. Correspondingly, having insertion loss above the target line at 0.85 dB defines the tuned filter. As shown in Fig. 7, both criteria are met, demonstrating that the filter is tuned.

The performance of the proposed algorithm has been evaluated

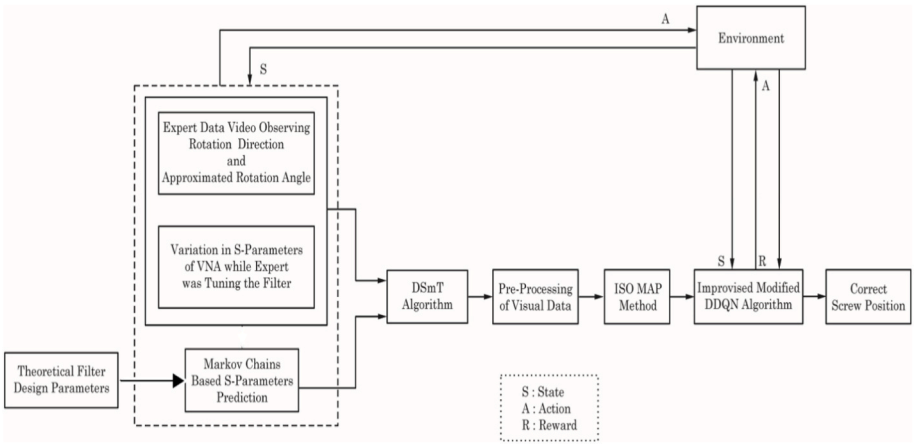

Fig. 4. AI and ML based Filter Tuning Algorithm.

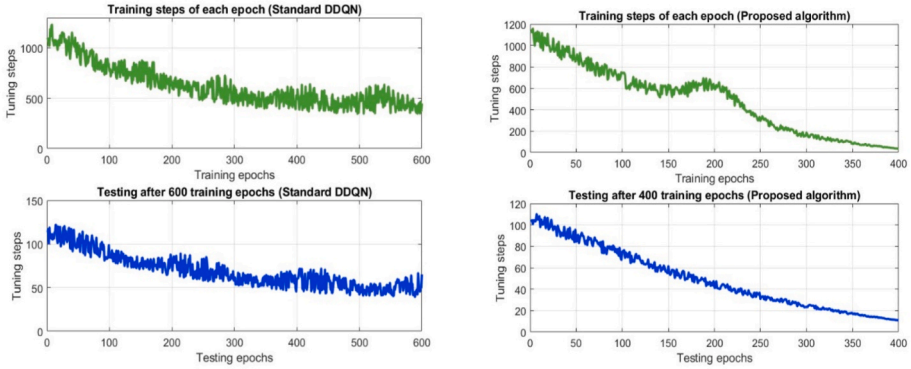

Fig. 5. Model training and testing results – Standard DDQN Algorithm v/s Proposed Algorithm.

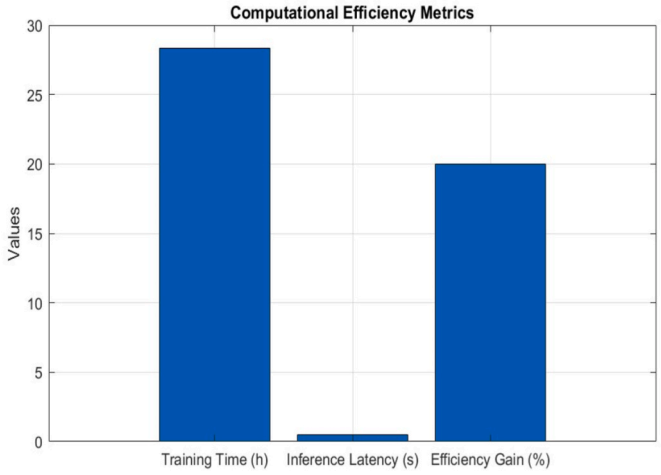

Fig. 6. Parameters of the proposed algorithm.

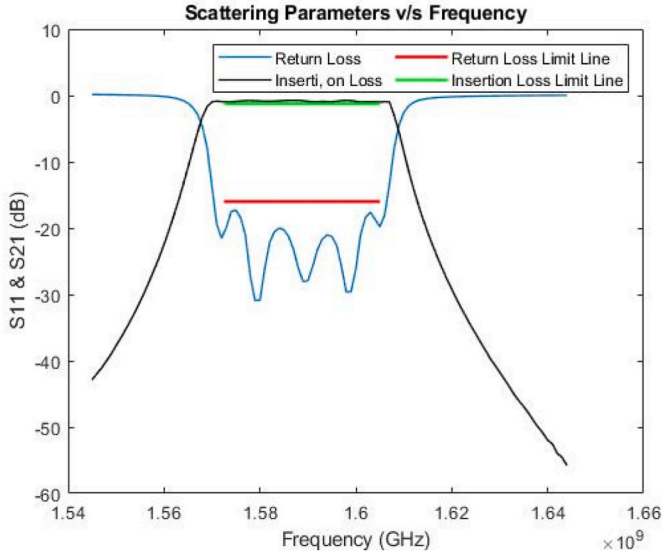

Fig. 7. Frequency response with the proposed algorithm.

against the best tuning curve achieved by human expert which acts as the target curve. These performance metrices used for this purpose are discussed in Table 8.

For finding the accuracy in reaching the target i.e. RLA and ILA, formulas (1) and (2) were used respectively.

Table 8
Considered performance matrices.

Parameter	Definition	Criteria
Return Loss Accuracy (RLA)	Difference between measured and target return loss (S_{11})	$< \pm 1$ dB
Insertion Loss Accuracy (ILA)	Difference between measured and target insertion loss (S_{21})	$< \pm 0.45$ dB
Prediction Accuracy of Proposed Algorithm (PA)	How well the proposed algorithm brought the S_{11} and S_{21} curves closer to the corresponding curves by the human expert	–
Tuning Success Rate (TSR)	Percentage of filters successfully tuned	Below −16 dB for S_{11} Above −0.85 dB for S_{21}

$$RLA = \frac{\sum_{i}^{n} \left(A_{S11_i} - T_{S11_i}\right)}{n} \tag{1}$$

where A_{S11_i} = Actual machine tuned value of S_{11} curve at i^{th} instance

T_{S11_i} = Target tuned value of S_{11} curve (achieved by human expert) at i^{th} instance

$$ILA = \frac{\sum_{t}^{m} \left(A_{S11_t} - T_{S21_t}\right)}{m} \tag{2}$$

where A_{S21_t} = Actual machine tuned value of S_{21} curve at i^{th} instance

T_{S21_t} = Target tuned value of S_{21} curve (achieved by human expert) at t^{th} instance

The prediction accuracy (PA) of the proposed algorithm was determined using (1)–(3).

$$A_{pred} = 100 - d(RLA) - d(ILA) \tag{3}$$

where $d(.)$ = decimal value of dB

The tuning success rate (TSR) was found using (4).

$$f(x) = \begin{cases} 1, S_{11i} < -16 \text{ dB and } 0.0001 < S_{21i} < -0.85 \; \forall \, i \in 1, y \\ 0, otherwise \end{cases} \tag{4}$$

where y = set of all the values constituting S_{11} and S_{21} curves

Table 9
Results of proposed algorithms.

Parameter	Results
RLA	+0.38 dB
ILA	−0.36 dB
PA	98 %
TSR	90 %

Based on (1)–(4), the results are presented in Table 9, and the corresponding graphs are presented in Fig. 8.

The proposed algorithm was compared against.

1. Traditional manual tuning by experts (baseline method), and
2. Standard DDQN algorithm

Comparative analysis showed that the proposed algorithm achieved the following results (also shown in Fig. 9).

1. Higher accuracy in achieving return loss target (95 % v/s. 85 % for DDQN). The manual tuning was taken as the baseline method as discussed earlier.
2. 50 % reduction in number of times the tuning screw was visited compared to the manual tuning.

The proposed algorithm inherently addresses uncertainties using Dezert–Smarandache Theory (DSmT), which fuses ambiguous or conflicting evidence from the camera-based observations and VNA data. The bias against uncertainties was analyzed using random perturbations in input S-parameter readings and rotational angle estimations. It was found that the proposed algorithm shows approx. $\pm$ 3.4% tolerance with $\pm$ 5% uncertainty when we computed and tuned nearly 25 filters of 5th-order. It is worth mentioning that all the filters exhibited variations in S_{11} and S_{21} curves.

The use of a proposed algorithm (based on Reinforcement Learning) introduces black-box behavior, limiting interpretability. As a limitation, the study acknowledges the need for Explainable AI (XAI) integration in future work. Techniques such as.

- SHAP (SHapley Additive exPlanations) for identifying influential features (e.g., screw position vs. S-parameter trend),
- LIME (Local Interpretable Model-Agnostic Explanations) for local decision analysis, and
- Grad-CAM (Gradient-weighted Class Activation Mapping) for visualizing CNN attention regions

could help in understanding decision pathways and improving transparency. Such XAI methods can be targeted in future works.

5. Conclusion

In conclusion, this research paper was aimed to review and synthesize the extensive body of work in the field of tuning the MW/RF communication filters. To this end, over 200 papers from various journals and conferences were diligently reviewed. While the paper primarily focused on frequency-domain studies, it also acknowledged time-domain research, showcasing the evolution and categorization of MW filter research. The study showcased that filter tuning is indeed a complex and resource-intensive process and to overcome bottlenecks in the efficient production of MW filters automating this process takes paramount importance. Further, the paper identified the key challenges in filter tuning and discussed the limitations associated with different topologies. The paper concludes with the proposal of a novel AI and ML-based method for tuning MW filters, demonstrating effectiveness in tuning a 5th-order all-pole cavity filter.

CRediT authorship contribution statement

Even Sekhri: Writing – original draft, Software, Formal analysis, Data curation. **Rajiv Kapoor:** Writing – review & editing, Visualization, Supervision, Project administration, Conceptualization. **Mart Tamre:** Validation, Resources, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests. Rajiv Kapoor reports administrative support was provided by Delhi Technological University Department of Electronics and Communication. Rajiv Kapoor reports a relationship with Delhi Technological University that includes: non-financial support. This work is being jointly taken up by me at Delhi Technological University and Dr Even

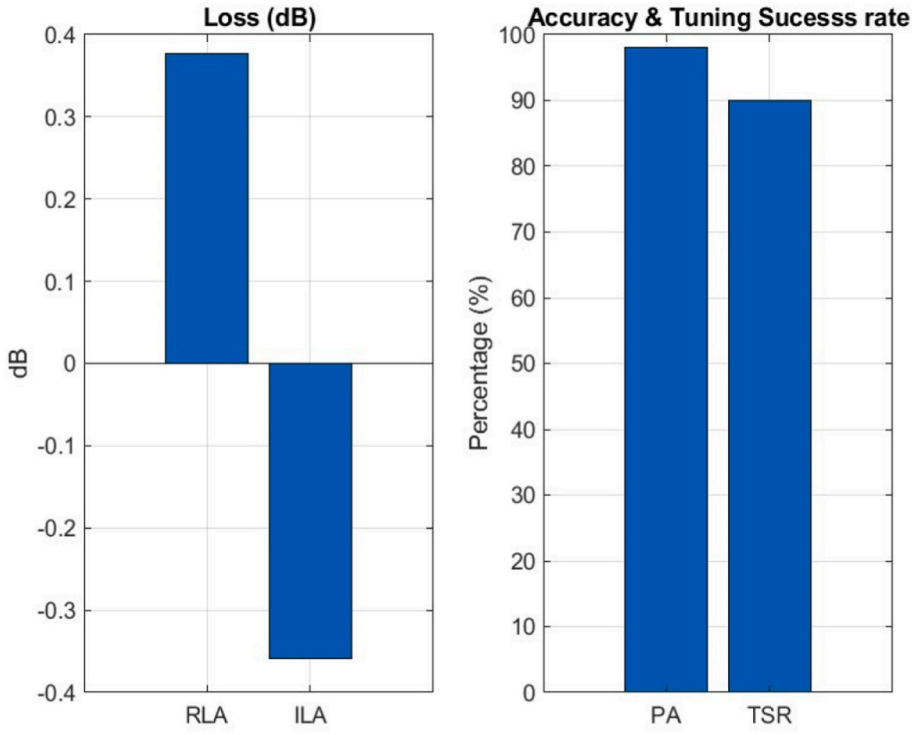

Fig. 8. Results of Parameters Evaluation of the proposed algorithm.

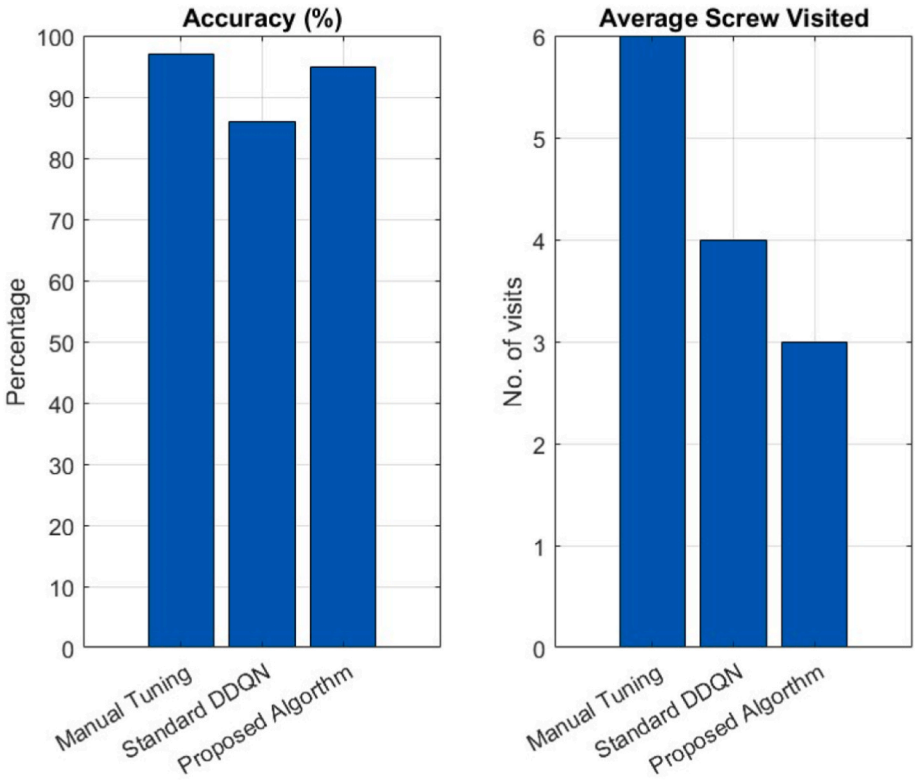

Fig. 9. Performance comparison.

Sekhri + Prof. Mart Tamre from Tallinn University of Technology, Estonia.

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Data availability

No data was used for the research described in the article.

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